

# Testing for Racial Discrimination in Bail Setting Using Nonparametric Estimation of a Parametric Model

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## Abstract

Black defendants are assigned greater bail levels than whites accused of similar offenses. To investigate whether this difference can be explained without taste-based discrimination, we construct a simple model of optimal bail setting. We develop a two-step econometric method that allows us to estimate the model while holding constant defendant heterogeneity that judges can observe, even when we do not. In return for making the behavioral model's relatively weak parametric assumptions, we are able to allow an arbitrary conditional distribution of such heterogeneity. We estimate the model using publicly available administrative data on felony defendants for five counties in 2000 and 2002. Point estimates suggest discriminatory bail levels in at least one, and possibly two, of these counties, where estimates suggest that judges set bail as if the value of blacks' lost freedom is less than two-thirds the value of whites' lost freedom. This result translates into a substantial black-white gap in the value of lost freedom—at least \$64 per day.

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# 1 Introduction

In this paper, we construct a simple model of judges' optimal bail setting that allows us to test for racial discrimination in bail levels. We show how to estimate a key parameter using a two-step econometric method. The first step involves nonparametric estimation of certain conditional choice probabilities. In the second step, we estimate an auxiliary projection equation whose variables are generated using the first step's nonparametric estimates. This second step yields a consistent estimate of a parameter,  $R^v$ , which is an increasing function of the value the judge implicitly places on the lost freedom of defendants who do not make bail. Our method allows for the model's systematic unobserved heterogeneity component with an arbitrary distribution, even conditional on observables. The price we pay for this generality is that we must specify a particular stochastic structure for defendants' behavior, conditional on all heterogeneity that judges observe.

A judge who follows the objective function we assume will choose bail to balance two kinds of marginal social costs against each other: the marginal expected social costs of holding a defendant until trial, and the marginal expected social costs that the defendant would impose on society if he is instead released pending trial. The social costs of jailing a defendant include both the pecuniary costs related to the physical jailing itself and the value the judge places on the defendant's lost freedom. A judge who is biased against blacks will value their freedom less than whites' freedom. Thus, the value of lost freedom is the variable through which any taste-based discrimination operates in our model.

We use the form of the judge's first-order condition to construct our second-step auxiliary projection equation. This equation allows us to estimate, via least-squares estimation, the parameter  $R^v$  mentioned above. This parameter is a function of the value of lost freedom, the pecuniary costs of jailing a defendant conditional on his not making bail, and the direct social costs imposed by a released defendant's failure to appear for trial. Under certain homogeneity assumptions concerning (i) the pecuniary costs of jailing the defendant, and (ii) the expected social costs of crimes committed by a released defendant pending his trial, black-white differences in  $R^v$  will be due only to differences in the value of lost freedom judges accord to blacks and whites.

To implement our auxiliary-equation approach, we require the information that enters the judge’s first-order condition. According to the model, this information includes both the levels and partial derivatives, with respect to bail, of two conditional choice probabilities: the probability that the defendant makes bail, and the probability that he fails to appear in court as ordered, given that he has made bail. The conditioning in these probabilities involves two types of defendant characteristics. The first type,  $x$ , includes those characteristics that both we and the judge observe. Examples of these characteristics include a host of criminal history variables, as well as the defendant’s age and the most serious offense with which he is charged. The second type,  $u$ , includes any defendant characteristics that judges can observe, but we cannot. We refer to  $u$  as unobserved heterogeneity (though we emphasize again that they are observable to the judge).

The existence of  $u$  complicates our task, because a judge who sets bail optimally uses information on defendants’ choice probabilities conditional on the bail level, on  $x$ , and on  $u$ . Estimating choice probabilities conditional on unobservable information would seem to be impossible. However, we show that when judges set bail optimally according to our model, conditioning simultaneously on  $x$  and the optimal bail level is sufficient to also condition on  $u$ . Intuitively, if defendants A and B facing the same charge have the same  $x$ , but a judge sets higher bail for A than B, then A must have unobservable characteristics that signal higher social costs of releasing him on bail. This basic idea is analogous to the key idea in Olley and Pakes’s (1996) study of production-function estimation, as well as in Altonji’s (1986) study of intertemporal labor supply.<sup>1</sup>

The informational equivalence result just discussed is useful given some structure on the form of heterogeneity in defendants’ latent utilities that neither we nor the judge observes.

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<sup>1</sup>Olley & Pakes construct a model in which firms have idiosyncratic productivity levels, which they observe but researchers do not, analogous to our  $u$  term. Olley & Pakes prove that investment is monotone in this unobserved productivity level. While their estimation method involves multiple steps, their core idea for our purposes is that observed investment can serve to control for unobserved productivity. Altonji (1986) estimates preference parameters in a model of intertemporal labor supply. In such models, labor supply depends on past and expected future wages, which researchers do not observe. However, if labor supply is chosen optimally, then a form of the labor supply function can be written so that all lagged and expected future prices enter labor supply only through the marginal utility of income, or “lambda”, which is analogous to the firm-level idiosyncratic productivity variable in Olley & Pakes. Altonji is able to allow lambda to evolve over time by using contemporaneous consumption as a control variable in a labor supply equation. Other work using related ideas includes Newey, Powell and Vella (1999) and Hotz and Miller (1993).

Along with  $x$ ,  $u$ , and the defendant’s bail level, the realized values of a vector of such “totally unobservable” heterogeneity terms,  $\epsilon$ , determine which of three options a defendant selects: (i) not making bail, (ii) making bail and appearing in court as ordered, or (iii) making bail and failing to appear. Judges must set bail when they know only the probability of each defendant’s choice, i.e., without knowing the value of the heterogeneity terms  $\epsilon$ . Given a Type I Extreme Value assumption, choice probabilities have a multinomial logit form conditional on bail,  $x$ , and  $u$ . That is convenient because partial derivatives of choice probabilities that have the multinomial logit form can be written as simple functions of the probabilities themselves. All of the data needed for the auxiliary regression described above thus involve conditional choice probabilities that can be estimated nonparametrically based on the one-to-one conditional relationship between  $u$  and the optimal bail level.

To estimate the model, we use data on five large counties for 2000 and 2002 from the State Courts Processing Statistics (SCPS) data set, which we discuss below. A nice feature of the econometric framework is that the judge’s preference parameters enter the auxiliary projection equation nonlinearly and redundantly. As a result, these parameters are overidentified. This allows us to test for model mis-specification by testing whether certain restrictions on the auxiliary equation’s parameters are violated. We find that they are not. In addition, after estimating the model’s parameters with its restrictions imposed, we find that all parameters have the signs expected under the model. Thus, our empirical results suggest that the model performs quite well in describing the data. We find that there is consistent, though often imprecisely estimated, evidence of discrimination against blacks in bail setting, especially for Harris county, Texas, and, depending on the specification, also for Dallas county. The magnitude of discrimination against blacks implied by our point estimates for these counties is substantial. Back-of-the-envelope calculations based on our point estimates suggest that black defendants’ lost freedom is valued at least \$64 per day less than white defendants’. Given the mean pre-trial period of 82 days in our data, this means judges in Dallas and Harris counties value the lost freedom of blacks held over for trial more than five thousand dollars less than they value white defendants’ lost freedom. Our results do not suggest discriminatory bail setting in Broward, Cook, or Los Angeles counties.

The remainder of the paper proceeds as follows. In section 2, we discuss existing literature

and provide some detail concerning bail policy and statutes. In section 3, we describe the SCPS data we use. In section 4, we present the basic theoretical model of judge and defendant behavior. We put some econometric structure on this model and discuss our estimation approach in section 5, and we report estimates in section 6. In section 7, we discuss the relationship of our model both to Ayres and Waldfogel’s (1994) and the recent literature on racial profiling and outcome tests in the context of roadside motorist searches. Finally, we conclude in section 8.

## 2 Bail Policy and Previous Literature

Historically, the sole purpose of pretrial detention was to ensure future court appearances. Judges decided bail levels primarily as a function of the offense charge, rather than the characteristics of individual defendants. Such a system causes poor defendants to be much less likely than wealthier ones to make bail.

In 1961, the Manhattan Bail Project was created in New York City to establish consistency in pretrial decisions while making pretrial outcomes less dependent on economic status. The results led to legislation that increased pre-trial release (Ares, Rankin and Sturz (1963)). The federal Bail Reform Act of 1966 laid out a set of standards for federal judges to follow when making pretrial release decisions for defendants in federal court. For the first time, this act established a prioritized list of options that a judge must follow, starting with release on recognizance.

In 1968, the American Bar Association published a set of standards elaborating on the Federal Bail Reform Act and adding two additional guidelines. First, when setting bail, judges should consider potential danger to the community of releasing a defendant. Second, the ABA recommended eliminating surety bail, in which a third party assumes responsibility for the defendant’s bail in return for a fee, due to a long history of perceived abuses. In 1970, the District of Columbia was the first jurisdiction to require judges to take into account the potential threat to the community along with flight risk when making their pretrial release decisions. Almost twenty years later, in 1984, the Federal Bail Reform Act was amended for the first time to allow federal judges to consider danger to the community

and preventative detention when making pretrial release decisions (Clark and Henry (1997)).

There is now virtual consensus that preventing flight and protecting the public are the primary goals of judges making pre-trial release decisions (Demuth (2003)). That said, statutes and procedural rules governing bail setting leave substantial room for judicial discretion. For example, Florida Rule of Criminal Procedure Rule 3.131(b) states in part that

(2) The judge shall at the defendant's first appearance consider all available relevant factors to determine what form of release is necessary to assure the defendant's appearance. If a monetary bail is required, the judge shall determine the amount....

(3) In determining whether to release a defendant on bail or other conditions, and what that bail or those conditions may be, the court may consider the nature and circumstances of the offense charged and the penalty provided by law; the weight of the evidence against the defendant; the defendant's family ties, length of residence in the community, employment history, financial resources, need for substance abuse evaluation and/or treatment, and mental condition; the defendant's past and present conduct, including any record of convictions, previous flight to avoid prosecution, or failure to appear at court proceedings; the nature and probability of danger that the defendant's release poses to the community; the source of funds used to post bail; whether the defendant is already on release pending resolution of another criminal proceeding or is on probation, parole, or other release pending completion of sentence; and any other facts the court considers relevant. *Florida Rules of Criminal Procedure, Rule 3.131.*

Bail statutes for the other states whose counties we study allow similar discretion.<sup>2</sup>

The pretrial process has received relatively little research attention from social scientists. Perhaps its earliest treatment in the economics literature was by Landes (1973), who models bail setting as an optimizing procedure. What criminological research does exist suggests that pretrial detention may have substantive welfare effects on defendants. Work by Goldkamp (1979) suggests that jailed defendants he studied were less able to build an adequate defense and therefore received more severe punishments. Goldkamp also found that the stigma of being in jail affected a case's outcome, especially if a jury trial was involved. Irwin

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<sup>2</sup>For example, Cal.Penal Code 1275(a) provides that "In setting, reducing, or denying bail, the judge or magistrate shall take into consideration the protection of the public, the seriousness of the offense charged, the previous criminal record of the defendant, and the probability of his or her appearing at trial or hearing of the case." Statutes for Illinois and Texas are available at 725 ILCS 5/110-5 and Texas C.C.P. Art. 17.15.

(1985) determined that any incarceration had negative effects on family and community ties, including employment, and ultimately stigmatized the defendant further. Clark and Henry (1997) state that defendants who were detained before trial were more likely to plead guilty, were convicted more often, and were more likely to receive a prison sentence than defendants who were released before trial. These concerns have recently received widespread media attention as part of a series on bail produced by National Public Radio (Sullivan (2010)). Other recent evidence suggests that bail burdens may weigh more heavily on disadvantaged racial and ethnic groups than on whites. Using administrative data from the State Courts Processing Statistics, Demuth (2003) finds that black and Hispanic defendants are about 20 percent more likely to be denied bail than whites. Black and Hispanic defendants are also more than twice as likely to be held on bail than are whites, even after adjusting for case characteristics.

Of course, these racial differences by themselves do not prove the existence of racial discrimination. Administrative data do not usually have information on drug use, employment or ties to community which may be considered relevant by the bail-setting judge (Smith, Wish and Jarjoura (1989)). Moreover, judges can observe defendants' in-court demeanor, whereas researchers usually cannot. Such unobserved factors may be associated with race, helping to explain the observed differences, and perhaps even totally explaining them.<sup>3</sup>

The two closest papers to this one are Abrams and Rohlfs (2010) and Ayres and Waldfogel (1994). Abrams and Rohlfs (2010) use data from the 1981 Philadelphia Bail Experiment to estimate key parameters and calibrate a model of optimal bail setting.<sup>4</sup> These parameters include the costs of jailing a defendant until trial, the defendant's value of lost freedom when jailed, and the social costs of any bad acts the defendant would commit while on release. Abrams and Rohlfs find that increasing a defendant's bail level reduces his probabilities of pre-trial release and of failing to appear or being rearrested while on release. Abrams & Rohlfs estimate the value defendants place on their own lost freedom, which they estimate

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<sup>3</sup>For example, some prior research using databases with richer measures of community ties and employment has found no race effects on pretrial release decisions (e.g., see Albonetti, Hauser, Hagan and Nagel (1989)).

<sup>4</sup>See Abrams and Rohlfs (2010) or Goldkamp and Gottfredson (1985) for details on this experiment. Colbert, Paternoster and Bushway (2002) conduct another experiment, involving representation by counsel in Baltimore. They find that being represented by counsel reduces bail levels, with no resulting impact on failure to appear.

at \$12 per day (they do not seek to estimate black-white differences in this value). This figure is considerably lower than the values our results suggest judges place on at least some defendants' lost freedom.

To our knowledge, Ayres and Waldfogel (1994) are the only other authors to study racial discrimination in bail setting through the lens of an economic model. Because Ayres and Waldfogel lack data on FTA, they develop a clever, market-based test for racial discrimination. They assume that judges seek to ensure appearance at trial with a minimum probability and show that this objective function implies that judges will set bail to equalize failure to appear rates across defendants. Using market data on bail bonds prices in New Haven, Connecticut, they find that blacks pay lower bond prices per dollar of bail. Under the assumption that the bail bonds market is competitive, this suggests the bail bonds market undoes judicial bias in bail setting: judges in the Ayres & Waldfogel sample hold blacks to a higher appearance-probability standard, which makes it cheaper to per dollar of bail bail to supply a bail bond to blacks than to whites.<sup>5</sup> We discuss their paper, and other related outcome-test work, in more detail in section 7.

## 3 Data

### 3.1 Basic data facts

The State Courts Processing Statistics (SCPS) dataset has been assembled biennially by the Bureau of Justice Statistics (BJS) since 1990. It is intended to represent the population of all felony cases brought in May in the 75 largest counties in the United States. The SCPS dataset follows cases from filing to disposition, or for one year—whichever occurs first.<sup>6</sup> It contains detailed information on the pretrial processing of felony defendants, including whether they are rearrested or fail to appear for a court hearing. It also contains important information on demographic, case, and contextual factors which may affect pretrial outcomes. In the analysis below, we use information on age at indictment, the offense category of the most serious

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<sup>5</sup>Helland and Tabarrok (2004) also consider issues related to bail. Their paper concerns the relative efficacy of public and private methods for finding those who have already failed to appear, which is a different topic from ours. Miles (2005) also considers re-capture of fugitives.

<sup>6</sup>Murder cases are followed for up to two years, but we do not include any of these cases in our analysis.



charge the defendant faces, previous criminal history (including arrest and incarceration), and whether the person was under criminal justice supervision (on bail, probation, or parole) at the time of arrest.

SCPS sampling is done in two stages. In the first stage, the 75 largest counties in the U.S. are divided into four strata based on population size, and 40 counties are chosen from these strata. In the second stage, the BJS chooses days in May, with more days chosen for smaller counties than larger ones. For the smallest counties, the BJS selects 20 business days, and for the largest counties, it selects only 5, at random. For each day in each selected county, the sample includes all felony defendants indicted on that day, and data are collected over the succeeding 12 months or until the case is disposed of.

The SCPS dataset includes weights that can be used to account for representativeness and inference issues that arise due to this multi-stage sampling process. However, we do not use these weights, for reasons we explain momentarily. We wish to estimate separate parameters of interest for each county we consider. After detailed work with the data, we found that many county-year cells in the SCPS had very small samples. Since parameter estimates for small counties would be very noisy, we exclude them. The five counties we do use are: Broward, Florida (which includes Ft. Lauderdale); Cook, Illinois (Chicago); Dallas, Texas; Harris, Texas (Houston); and Los Angeles, California. All are in the largest stratum, which means that they were selected with certainty each year of the survey, and had cases from five days during May selected.<sup>7</sup>

Pretrial policies vary across these counties. Illinois is one of four states that ban commercial bail bonds companies, so bail is handled directly by the court in Cook County. On the other hand, Texas historically has encouraged the use of commercial bail bondsmen. In Harris County, groups backed by bail bonds groups tried to get rid of non-bail pretrial release programs in the mid-1990s; these efforts were ultimately unsuccessful. A similar attempt was successful in Broward County, but not until 2009, after our data were collected (Sullivan

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<sup>7</sup>Prior to 2000, Broward was in the second largest stratum, which means it had had .55 chance of being selected for the survey, and cases from 10 days were selected. This is one reason we do not use data from 1998 or earlier. Another involves data issues with Los Angeles, for which many observations have missing data on race for 1998. In addition, Cook county has a substantially lower share of potential 1998 observations, by comparison to Dallas and Harris, than it does for 2000 and 2002. This raises questions about sample comparability across these years. These issues, together with Broward's change in stratum, have convinced us to drop 1998 altogether.

(2010)).

To select our sample, we used the following algorithm. We first dropped all observations involving a pre-2000 indictment. Next, we kept only cases in which the defendant’s race was recorded as either black or white, and we dropped all cases with a defendant reported to be of Hispanic background. We then kept only those cases in which the defendant was assigned positive bail. We dropped all cases in which the most serious charge was murder, since defendants in murder cases are followed twice as long by the SCPS as are other defendants; because there are comparatively few murders in the sample, this selection choice likely makes no difference to our results. For the remainder of the paper, we refer to the most serious charged offense as simply the charged offense; note, though, that defendants can be charged with multiple offenses. We divide defendants into those charged with violent, property, drug, and public order offenses. These categories have the following constituent offenses:

- **Violent crimes:** rape, robbery, assault, “other violent.”
- **Property crimes:** burglary, larceny-theft, motor vehicle, theft, forgery, fraud, and “other property.”
- **Drug crimes:** drug sales, “other drug.”
- **Public order crimes:** weapons, driving-related, “other public order.”

Table 1 reports some basic summary statistics for the data we use in the analysis below. The first two columns of the table report descriptive statistics for blacks and whites charged with a violent crime. Average bail for blacks charged with violent crimes is roughly \$36,000, about \$7,000 greater than the average bail assigned to whites charged with these crimes. One consequence of the higher average bail facing blacks charged with violent offenses is that only 40% of them made bail, by comparison to 53% of whites charged with violent offenses.

A naive approach to testing for discrimination would take the \$7,000 difference in bail for defendants charged with violent offenses as evidence of anti-black bias. However, blacks and whites accused of violent crimes differ in many ways. For example, the “Any prior FTA” row shows that 32% of the blacks in the sample have previously failed to appear in court, by

comparison to only 21% of whites. Additionally, 26% of blacks in the violent-offense category could not have previously failed to appear, meaning that they were not previously ordered to appear in court; among whites, this figure is 33%. Blacks charged with violent crimes also were more likely than whites to have been arrested previously (74% versus 67%), and more of them had been arrested at least ten times (22% versus 16%). They were also more likely to have previously served time in prison (24% versus 18%, though roughly the same share of blacks and whites had previously served time in jail—45% versus 44%), and they were also twice as likely to have an active criminal justice status at the time of charging. In addition, blacks facing a violent-offense charge were less likely to be represented by a private attorney, with black-white differences in the share represented by public defenders accounting for most of this difference.<sup>8</sup>

As with violent offenses, blacks charged in the other three offense-type categories also face higher bail levels than do whites. These differences are especially large for drug crimes (about \$13,000) and public order crimes (more than \$10,000). Blacks charged in these three categories are also much less likely than whites to make bail. As with those charged with violent crimes, blacks in the other three categories uniformly have more extensive criminal-justice backgrounds than whites, as measured by the variables considered in Table 1.

### 3.2 Regression-adjusted bail differences

These differences in criminal background suggest that simple differences in average bail by racial group are problematic measures of discrimination: it is possible that whites with the same characteristics as blacks in the sample would receive the same bail. A conventional approach to adjusting for characteristics is to estimate the black-white difference in average bail by estimating a linear regression model in which background characteristics enter as

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<sup>8</sup>We do not include information about attorney type in our estimation of defendants' conditional choice probabilities. While we would like to do so, we found that observations with missing attorney-type differed systematically from those with non-missing data. For example, those missing attorney-type data are much more likely to come from Broward than from other counties; are 14 percentage points more likely to FTA for blacks, but only 3 points more likely for whites (these figures are conditional on having made bail); are 30 points more likely to make bail for whites and 36 points more likely to make bail for blacks; and have lower mean bail amounts by more than \$4,000 for whites, and more than \$7,000 for blacks. Perhaps as a consequence, we found that preliminary results were sensitive to restricting estimation to those observations with non-missing attorney-type data (whether or not we used attorney type as an  $x$  variable). Under the circumstances, we believe the best approach is to disregard attorney-type data.

covariates. We report the coefficient on a dummy variable indicating that the defendant is black in the second row of Table 1. For violent crimes, this coefficient is roughly -\$140, suggesting that blacks' bail is actually slightly lower than whites after regression adjustment, which obviously does not support the hypothesis of discrimination against blacks. For the other offense-type categories, regression-adjusted differences are much smaller than raw black-white differences.<sup>9</sup>

Such a simple approach to controlling for defendant differences is of limited use, for two reasons. First, even if the coefficient on the race dummy could otherwise be interpreted as the causal difference in average bail due to being black rather than white, there is the problem of unobserved heterogeneity. If judges observe heterogeneity in defendants that researchers cannot, and if this heterogeneity varies systematically with race conditional on the other covariates, then the race-dummy coefficient cannot be interpreted as the causal effect of defendant's race on bail.<sup>10</sup> Second, without unobserved heterogeneity, plausible behavioral models might not yield a simple linear regression model for bail. The simple behavioral model we analyze below generally does not, for example.<sup>11</sup> Another approach would be to use more flexible matching methods to compare conditional bail levels across race. However, under our behavioral model, this method fails if there is unobserved heterogeneity, because then blacks and whites with the same observable characteristics will not generally fail to appear with the same probability. For these reasons, we do not pursue either simple regression estimators or matching estimators further.

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<sup>9</sup>There is no support for the hypothesis that blacks are favored, either, as the estimate's p-value against the two-sided null of no effect is 0.95.

<sup>10</sup>This problem could be solved in principle via random assignment of defendant's race, but this solution seems impractical. Defendant's demeanor in court is one important source of heterogeneity observed by judges but not researchers. How would one assign race randomly conditional on such behavior? Audit studies based on written case files would have the related problem of lacking the realism of in-court events. Heckman and Siegelman (1993) discuss other issues related to audit studies.

<sup>11</sup>Interestingly, it can be shown that the judicial objective assumption that Ayres and Waldfogel (1994) assume, when married to our reduced form model of defendant's behavior, yields an optimal bail function that is affine in the heterogeneity term  $u$  and a potentially nonlinear function,  $g_2$ , of the  $x$  characteristics observed by both judges and researchers. If  $u$  is assumed to be distributed identically across race and  $g_2$  has the same constant term for both races, then a partial regression coefficient approach can be shown to identify a measure of discrimination in bail setting. However, the racial homogeneity assumptions on  $u$  and  $g_2$  are both quite strong, and our method does not require them.

### 3.3 Conventional outcome tests

The “FTA, given made bail” row of Table 1 reports the fraction of defendants who failed to appear as ordered, given that they made bail (notice that this means the risk set is endogenous to whether a defendant makes bail). Because we have data on this variable, we can use Ayres and Waldfogel’s (1994) outcome test without requiring any of the bail-bond information they cleverly use. Table 1 shows that 10% of blacks who make bail fail to appear, by comparison to 14% of whites. While this difference is in the direction of anti-black bias according to AW’s test, it is not statistically significant: the standard error of the 3.8 percentage-point difference is 4.7 percentage points. Thus, among those charged with violent offenses, we would fail to reject the null hypothesis of no discrimination against blacks using AW’s outcome test. Interestingly, among those charged with drug offenses, blacks actually FTA more often than whites—25% by comparison to 20%. The AW outcome test would thus conclude that for those accused of drug crimes, blacks are favored in bail-setting relative to whites. However, this difference is again statistically insignificant.<sup>12</sup> We discuss the relationship between our approach and conventional outcome tests in more detail in section 7.

### 3.4 County-specific differences in bail

In Table 2, we provide another cut of the raw bail data by reporting average bail for each county and race group. There are two notable features of these data. First, average bail levels are much lower in Broward, Dallas, and Harris counties than for Cook or Los Angeles. Second, only Cook and Los Angeles have statistically significant differences in bail levels across race, with blacks assigned systematically higher bail levels.

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<sup>12</sup>Even accepting this method for testing discrimination, though, the results just described are for a sample of defendants pooled across several different counties. Judges in different counties might be differently prejudiced, so we do our main analysis separately by county below.

## 4 Model

### 4.1 Basic setup

We assume the judge's objective is to minimize social costs, defined momentarily, and we consider the stage of the case when her only choice variable is  $b$ , the amount of bail that she sets. Let  $\theta = (x, u)$  be a signal concerning the defendant's type. We assume that the judge can observe this entire signal, while researchers generally can observe only  $x$ . We define the conditional probability that the defendant makes bail, given the bail amount  $b$ , as  $M(b, \theta)$ . For each  $\theta$ , we assume there exists some  $b^{\max}$  such that the probability  $M(b, \theta)$  is strictly decreasing in  $b$  for all  $b \in [0, b^{\max}]$ , with  $M(0, \theta) = 1$ ,  $M(b, \theta) \in (0, 1)$  for all  $b \in (0, b^{\max})$  and  $M(b, \theta) = 0$  for all  $b \geq b^{\max}$ . Since defendant's wealth is finite, it is therefore always mathematically feasible for the judge to choose a bail level sufficiently great that the defendant cannot make bail.

If the defendant does not make bail, then the state will incur pecuniary jailing cost  $P$ ; this cost does not vary with either the amount of bail the judge chooses or the defendant's type  $\theta$ . In addition, the defendant will lose his freedom. We denote with  $V(\theta)$  the value the judge places on the lost freedom of a type- $\theta$  defendant; notice that  $V$  does not vary with the level of bail. While our notation allows  $V$  to vary with all defendant characteristics, we assume below that this parameter varies only with defendant's race and county.<sup>13</sup> Race-based discrimination occurs when a judge values defendants' lost freedom differently as a direct function of defendants' races. This means that a judge who values blacks' lost freedom less than whites' acts as if  $V^{\text{black}} < V^{\text{white}}$ , so that the subjective costs of jailing blacks are lower than the costs of jailing whites, other things equal.

Next, we define  $S(b, \theta)$  as the expected social costs due to bad acts that a type- $\theta$  defendant will commit if he is released on bail. We assume that the conditional-on-release social costs function can be written

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<sup>13</sup>A more complex and ambitious model would allow the costs of lost freedom to include the opportunity cost of defendants' lost earnings, which would vary across defendants. We ignore this issue for tractability, and also because we do not have earnings data.

$$S(b, \theta) = C(\theta) + \phi F(b, \theta), \quad (1)$$

where  $F(b, \theta)$  is the probability that a type- $\theta$  defendant fails to appear given bail level  $b$ . The function  $C$  represents the expected social cost of crimes that a type- $\theta$  defendant will commit while out on bail. We assume that this expected cost may be written

$$C(\theta) \equiv c\rho(\theta),$$

where  $\rho(\theta)$  is the probability that a type- $\theta$  defendant will be rearrested while on release and  $c$  is the average cost of crime associated with an arrest. The parameter  $\phi$  can be thought of as the expected social cost associated with a defendant's failure to appear. One such cost is the pecuniary costs associated with finding the defendant. Another is the implicit cost that occurs because defying a valid judicial order to appear in court demonstrates disrespect for the criminal justice system and the courts. A third type of cost arises because of the havoc in courts' scheduling that FTA causes.

## 4.2 The optimal level of bail

The judge has three options: (i) release the defendant on his own recognizance, i.e., set bail equal to zero, (ii) set bail at or above  $b^{\max}$  so as to prevent release,<sup>14</sup> and (iii) set bail somewhere in the middle, allowing the defendant probability  $M(b, \theta) \in (0, 1)$  of obtaining his release. Because they are the only ones we study empirically, we focus here only on interior-optimum cases. This focus poses no selection problems, provided that our econometric model is otherwise specified correctly.

Suppressing the  $\theta$  parameter, the judge's decision problem is to

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<sup>14</sup>We think of denying bail as setting  $b = \infty$ . The statutes discussed above generally suggest that judges should not do so without good reason, however. For example, Texas's statute states that "The power to require bail is not to be so used as to make it an instrument of oppression." Texas C.C.P. Art. 17.15.

$$\begin{aligned}\min Q(b) &\equiv M(b)\{c\rho + \phi F(b)\} + [1 - M(b)](P + V) \\ &= M(b)[\phi F(b) - (P + V - c\rho)] + P + V.\end{aligned}$$

Next, we observe that since  $\phi > 0$ , and since  $P$  and  $V$  do not depend on  $b$ , we can focus attention on the increasing affine transformation of  $Q(b)$  given by

$$q(b) \equiv M(b)[F(b) - R], \quad (2)$$

where the parameter  $R$  is given by

$$R \equiv \frac{P + V - c\rho}{\phi} \quad (3)$$

(note that since  $\rho$  varies with defendant type,  $R$  will as well). Differentiating the right hand side of (2) with respect to  $b$  yields the first-order condition

$$M_b(b^*)[F(b^*) - R] + M(b^*)F_b(b^*) = 0. \quad (4)$$

Finally, we observe that  $R = R^v + R^c\rho$ , where

$$R^v \equiv \frac{P + V}{\phi} \quad \text{and} \quad R^c \equiv \frac{-c}{\phi}.$$

Observe that since  $P$ ,  $V$ ,  $\phi$ , and  $c$  are all positive by assumption,  $R^v > 0 > R^c$ .<sup>15</sup>

We show in Theorem 1 of Appendix A that under reasonable assumptions, the parameters  $R^v$  and  $R^c$  are identified for each subset of the population within which all of their underlying

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<sup>15</sup>In addition,  $R$  must be positive. We assumed above that  $M_b < 0$ , and we also assume that  $F_b < 0$  for all  $b$ , since the defendant will lose his bail when he fails to appear. Given that  $0 < M(\bullet) < 1$  for a positive and finite bail level, the second term in (4) must be negative. Therefore, the first term must be positive, so  $R > F(b^*)/0$  at the optimal bail level.



parameters— $P$ ,  $V$ ,  $\phi$ , and  $c$ —are constant. That result is not strong enough to identify the parameter of primary interest,  $V$ , without external knowledge of  $P$  and  $\phi$ . Even so, it is reasonable to assume that within county, the daily pecuniary cost of jailing a defendant before trial does not vary with race. It is also reasonable to think that the per se social costs of a failure to appear,  $\phi$ , do not vary with race within county. Under these assumptions, the only cross-race variation in  $R^v$  must be due to racial differences in  $V$ , the value of lost freedom. Thus, we can test the null hypothesis that bail is set optimally in a non-discriminatory fashion by testing the null hypothesis  $H_0 : R^{v,\text{black}} - R_w^{\text{white}} = 0$  against the alternative hypothesis  $H_a : R^{v,\text{black}} - R_w^{\text{white}} < 0$ . This is the test of discrimination we offer in this paper.

Using individual variation in estimated rearrest rates, we are able to estimate separate within-county values of  $R^c$  by race. Thus, we need not and do not impose cross-race equality in  $c$ , the social costs of crime associated with a rearrest.

We now turn to our econometric specification.

## 5 Econometric Specification

### 5.1 The basic econometric model

Let  $1(\bullet)$  be the indicator function, and let  $D_m = 1(\text{defendant makes bail})$  and  $D_f = 1(\text{defendant fails to appear})$ . Because the defendant cannot fail to appear if he does not make bail, there are only three possible outcomes to consider:

0. A defendant does not make bail:  $D_m = 0$ .
1. He makes bail and does not fail to appear:  $D_m = 1$  and  $D_f = 0$ .
2. He makes bail and fails to appear:  $D_m = 1$  and  $D_f = 1$ .

Where appropriate, we will use subscripts “0” to refer to the first event, “1” to refer to the second, and “2” to refer to the third. Additionally, we define the discrete dependent variable  $D$  that takes on values in  $\{0, 1, 2\}$  given each outcome, so that

0.  $\Pr(D = 0) = \Pr(D_m = 0)$
1.  $\Pr(D = 1) = \Pr(D_m = 1 \text{ and } D_f = 0)$
2.  $\Pr(D = 2) = \Pr(D_m = 1 \text{ and } D_f = 1)$

We assume that for a defendant with bail level  $b$  and characteristics  $(x, u)$ , latent utility in each of the three states just defined can be written as

$$\begin{aligned}
 V_0 &= \gamma_0 \ln b + g_0(x) + \epsilon_0 \\
 V_1 &= \epsilon_1 \\
 V_2 &= \gamma_2 b + g_2(x) + u + \epsilon_2.
 \end{aligned} \tag{5}$$

The event that  $D = 0$  is the event that  $V_0 > \max[V_1, V_2]$ ; the event that  $D = 1$  is the event that  $V_1 > \max[V_0, V_2]$ ; and the event that  $D = 2$  is the event that  $V_2 > \max[V_0, V_1]$ . In (5), we have normalized to zero the systematic part of utility in the  $D = 1$  case (defendant makes bail and doesn't FTA). Also, while conventional approaches involve intrinsically linear parameterizations of the functions  $g_0$  and  $g_2$ , we do not need to impose any functional form on them.

Since higher bail levels increase the probability of not making bail, we expect (but do not impose) that  $\gamma_0 > 0$ . Defendants should make bail with probability one when  $b = 0$ , so we assume that the bail level enters  $V_0$  in log form; in this case, the latent utility of not making bail is  $-\infty$ . Since defendants will not always fail to appear when bail is 0, we assume that bail enters  $V_2$  linearly. Since higher bail should serve as a deterrent to FTA among those who do make bail, we expect (but do not impose) that  $\gamma_2 < 0$ . We assume that  $u$  has mean zero in the population, which is innocuous given the presence of the nonparametric function  $g_2$ .<sup>16</sup>

Finally, consider  $\epsilon_0$ ,  $\epsilon_1$ , and  $\epsilon_2$ , which are the components of indirect utility that neither we nor the judge can observe. We assume that these terms are distributed jointly as Type I

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<sup>16</sup>Another point concerns our exclusion of  $u$  from  $V_0$ . This exclusion is not just a normalization, as it would be if  $u$  appeared in  $V_1$  as well as  $V_2$ . We have not proved the model's identification when  $u$  enters  $V_0$ . However, our empirical method would be unaffected by this extension—it would simply extend the domain of models for which our empirical work would be appropriate.

Extreme Value, so that the model has a multinomial logit structure, conditional on  $b$ ,  $x$  and  $u$ . This assumption implies that

$$Pr(D = 0|b, x, u) = \frac{\exp[\gamma_0 \ln b + g_0(x)]}{\exp[\gamma_0 \ln b + g_0(x)] + 1 + \exp[\gamma_2 b + g_2(x) + u]} \quad (6)$$

$$Pr(D = 1|b, x, u, D \neq 0) = \frac{1}{1 + \exp[\gamma_2 b + g_2(x) + u]} \quad (7)$$

$$Pr(D = 2|b, x, u, D \neq 0) = \frac{\exp[\gamma_2 b + g_2(x) + u]}{1 + \exp[\gamma_2 b + g_2(x) + u]}. \quad (8)$$

The first line shows that the conditional probability that the defendant doesn't make bail,  $1 - M(b, x, u)$ , is given by the standard formula for a multinomial logit probability when the option in question belongs to a different nest from all other options. The second and third lines show that, conditional on the event that the defendant makes bail—so that  $D \neq 0$ —the conditional probability that he doesn't ( $D = 1$ ) or does ( $D = 2$ ) fail to appear is given by a standard binary logit model. The multinomial logit assumption is convenient, in that it allows tractable closed-form formulas for relevant conditional choice probabilities and their partial derivatives. However, other structures would also work.<sup>17</sup> Finally, we note that from the perspective of researchers, the presence of heterogeneity in  $u$  means that the defendant's conditional choice probabilities do not have a multinomial logit form, so we are imposing the independence of irrelevant alternatives only conditional on  $u$ .

## 5.2 Estimation

The only unconventional aspect of (5) is the presence of the term  $u$  in the specification of  $V_2$ . This term represents any defendant-specific heterogeneity that can be observed by bail-setting judges but not by us. For example, judges can observe a defendant's behavior in

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<sup>17</sup>For example, we have proved that a generalized version of the empirical method we use here is valid when  $(\epsilon_0, \epsilon_1, \epsilon_2)$  have a Generalized Extreme Value distribution, so that the probabilities have a nested logit form. This result allows  $\epsilon_0$  to be independent of the dependent pair  $(\epsilon_1, \epsilon_2)$ . The unique mapping lemma that we prove in Appendix A holds provided that the degree of dependence in  $(\epsilon_1, \epsilon_2)$  is not too great. In addition, we conjecture that we could allow  $\epsilon_0$  to be normal and  $(\epsilon_1, \epsilon_2)$  to have a bivariate-normal distribution with unrestricted correlation coefficient, provided that  $\epsilon_0$  and  $(\epsilon_1, \epsilon_2)$  are independent. Our key requirement is only that, given that relevant conditional choice probabilities are known, their partial derivatives with respect to bail can be found, analytically, up to a finite number of parameters.

the courtroom during the hearing, which we cannot. Observable unruliness in court might be a good signal that a defendant is unlikely to appear in court except when he faces a high bail level. Good behavior plausibly has the opposite signal value. Other aspects of the defendant's background that we cannot observe might also be observable to the judge; examples include community ties, having a job, and so on.

Given that judges choose bail according to the first order condition (4), a defendant's observed bail will be a function of all the other elements of the model: the parameters  $(P, V, \gamma_0, \gamma_2, c, \phi)$ , the defendant's characteristics vector  $x$ , the functions  $\rho$ ,  $g_0$  and  $g_2$ , and the unobservable heterogeneity term  $u$ . First consider the case when  $u = 0$  for all observations, so that judges observe nothing more than we do. Then letting  $\Theta \equiv \{P, V, \gamma_0, \gamma_2, c, \phi, \rho, g_0, g_2\}$  be the set of all parameters and functions that characterize defendant and judge preferences, optimal bail may be written as  $b = b^*(x; \Theta)$ . The fact that judges choose the level of bail to minimize expected social costs would have no bearing on estimation via maximum likelihood in this case, provided that we and the judge both know  $\Theta$ . Intuitively, when we conditioned on  $x$  in forming the likelihood function, we would implicitly also be conditioning on bail, since optimal bail depends only on  $x$  and  $\Theta$  given fixed  $u$ . Conditioning on observed bail thus would add no further information and so could not cause any problems for estimation.

But with heterogeneity in  $u$ , the optimal bail function depends on both  $x$  and  $u$ , i.e.,  $b = b^*(u, x; \Theta)$ . So, conditioning on  $x$  is no longer sufficient to condition on  $b$ . If we observed  $u$ , we could condition on it in forming the likelihood, and we could then use maximum likelihood estimation, given parameterizations of  $g_0$  and  $g_2$ . This avenue is blocked since we cannot observe  $u$ , though, and the likelihood function will be mis-specified if we ignore it. Moreover, since bail is chosen optimally as a function of  $x$  and  $u$ , there will be dependence in the joint distribution of  $b$ ,  $x$  and  $u$ . The structure of this dependence will be functionally unknown even given knowledge of  $g_0$  and  $g_2$ . This makes otherwise attractive methods like Mroz's (1999) discrete-factor approach problematic, and possibly intractable.

Another alternative would be to specify a distribution for  $u$  and use numerical methods to simulate the likelihood. One could then use grid-search methods to calculate the optimal bail directly for each observation and then choose the parameters of  $R(\theta)$  either to minimize a criterion function or to match moments of the data. An advantage of this class of approaches

is that it would allow us to add more heterogeneity terms. However, they would also require us to specify conditional distributions of the heterogeneity terms given  $x$ .

Our approach is motivated by the fact—which we prove in appendix A—that there is a one-to-one mapping between the level of optimal bail and the heterogeneity term  $u$  under our model. Intuitively, a defendant with higher  $u$  has higher utility of failing to appear and is thus more likely to FTA at a given bail level. We would expect a rational judge facing two defendants with the same  $x$  but different  $u$  values to assign a greater bail level to the defendant with greater  $u$ . This result must be proved, though, because when the judge increases the bail level, probability shifts from the event that a defendant makes bail and does not FTA, to the event that he does not make bail in the first place. This increase in the probability of not making bail brings higher expected jailing costs, so the judge’s optimal response to an increase in  $u$  thus involves costs on both sides of the ledger.

Given the multinomial logit functional form for conditional choice probabilities, it can be shown that, given  $x$ , every optimal bail level maps to a unique value of  $u$ . More precisely, suppressing notation related to the model’s other parameters, let  $b^*(u; x)$  be the optimal bail level given  $(x, u)$ . In Lemma 1 of appendix A, we show the unique-mapping result that there exists a function  $h$  such that  $u = h(b^*(u; x); x)$ .

If we could find a closed form representation of the function  $h$  known up to a finite parameter vector, then we could use a standard control-function approach, substituting  $h(b; x)$  for  $u$  and then estimating the parameters of the defendant’s choice decision using maximum likelihood. However, inspection of the first order condition, as well as some fruitless attempts on our part, suggests that this approach is unlikely to work in general. Instead, we use the unique-mapping lemma referenced just above. Observe that the information set  $\{x, b^*\}$  is sufficient for the information set  $\{x, b^*, h(b^*; x)\}$ , given  $(\gamma_0, \gamma_2, g_0, g_2)$ . Therefore, conditioning on  $\{x, b^*\}$  is as good as conditioning on  $\{x, b^*, u\}$ .<sup>18</sup>

Define  $m(b, x) \equiv \Pr[D_m = 1|x, b]$  and  $f(b, x) \equiv \Pr[D_m = 1, D_f = 1|x, b]$ . These functions differ from their capital-letter counterparts in that the lower-case functions do not involve conditioning on  $u$ . By the unique-mapping lemma, however, for each  $d \in \{0, 1, 2\}$ , the

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<sup>18</sup>Note that this result does not generally hold for non-optimal levels of bail: if  $b'$  is not the optimal bail level given  $(x, u)$ , then  $u \neq h(b'; x)$ , so  $\{x, b', u\}$  contains more information than  $\{x, b'\}$ .

conditional probability that the defendant chooses  $D = d$  at the judge's optimum, given  $(x, b^*)$ , satisfies the following ignorability condition:

$$\begin{aligned}\Pr [D = d|x, b^*] &= \Pr [D = d|x, b^*, h(b^*; x)] \\ &= \Pr [D = d|x, b^*, u].\end{aligned}\tag{9}$$

As a result, it follows that

$$m(b^*, x) = M(b^*(u; x), x, u) \quad \text{and} \quad f(b^*, x) = F(b^*(u; x), x, u).\tag{10}$$

Given knowledge of the joint distribution of  $(b, x)$ , the functions  $m(b, x)$  and  $f(b, x)$  are nonparametrically identified, even without knowing anything about  $u$  or its distribution. Under the assumption that judges choose bail optimally, the relevant joint distribution involves the optimal bail level, i.e.,  $(b^*, x)$ , we can identify  $m(b^*, x)$  and  $f(b^*, x)$ . Thus, under the assumption that the judge chooses bail optimally,  $M(b^*(u; x), x, u)$  and  $F(b^*(u; x), x, u)$  are nonparametrically identified without any separate knowledge of  $u$  or its distribution. We establish this fact formally in Theorem 1, which we state and prove in Appendix A.<sup>19</sup>

The next step in demonstrating identification of  $R^v$  and  $R^c$  is to show how to rewrite the judge's first-order condition entirely in terms of the optimal bail level and the conditional choice probabilities  $m(b^*, x)$  and  $f(b^*, x)$ . This is possible using the well known fact that derivatives of multinomial logit conditional choice probabilities are fully determined by the choice probabilities themselves, up to a finite number of unknown parameters. Differentiating (6) and (8) partially with respect to the bail level and engaging in a large amount of tedious algebra, it can be shown that for any  $(b, x, u)$ ,

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<sup>19</sup>For theoretical completeness, we also establish identification of  $(\gamma_0, \gamma_2)$ , as well as point identification of the function  $g_0(x)$ . The function  $g_2(x)$  is not identified, although the sum  $g_2(x) + u$  is. In addition, it is possible to identify differences in  $u$  across two observations having the same value of  $x$ . We do not use these identification results in our empirical work, however.

$$M_b(x, b, u) = \left[ \gamma_2 F(b, x, u) - \frac{\gamma_0}{b} \right] [1 - M(b, x, u)] M(b, x, u), \quad (11)$$

and

$$F_b(b, x, u) = \gamma_2 F(b, x, u) [1 - F(b, x, u)]. \quad (12)$$

By the ignorability condition (9), all conditioning on  $u$  is extraneous in the defendant's conditional choice probabilities at the optimal bail level  $b^*(u; x)$ . Thus, we can replace  $M(b^*, x, u)$  and  $F(b^*, x, u)$  in (11) and (12) with  $m(b^*, x)$  and  $f(b^*, x)$ . Fixing  $x$  and  $u$  and writing  $m^* = m(b^*, x)$  and  $f^* = f(b^*, x)$ , it follows that (11) and (12) can be re-written at their optimal values as<sup>20</sup>

$$M_b^* = \left( \gamma_2 f^* - \frac{\gamma_0}{b^*} \right) (1 - m^*) m^* \quad (13)$$

$$F_b^* = \gamma_2 f^* (1 - f^*), \quad (14)$$

Plugging these first derivatives' values into the first-order condition (4), we now have as the necessary condition for optimality that

$$m^* \gamma_2 f^* (1 - f^*) + \left[ \gamma_2 f^* - \frac{\gamma_0}{b^*} \right] (1 - m^*) m^* \{f^* - R\} = 0. \quad (15)$$

This form shows that for given values of  $\gamma_0$ ,  $\gamma_2$ , and  $R$ , the first-order condition can be written in closed form as a function of the optimal bail level and the (identified) conditional choice probabilities  $m^*$  and  $f^*$ . Dividing (15) by  $\gamma_2$ , moving terms to the right-hand side, and regrouping then yields

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<sup>20</sup>For notational ease, we leave implicit the empirically important fact that  $m^*$  and  $f^*$  vary with  $x$ .

$$\begin{aligned}
m^* f^* (1 - m f^*) = & \left[ \frac{(1 - m^*) m^* f^*}{b^*} \right] \frac{\gamma_0}{\gamma_2} \\
& + \left[ (1 - m^*) m^* f^* \right] R \\
& + \left[ \frac{(1 - m^*) m^*}{b^*} \right] \left( -\frac{\gamma_0}{\gamma_2} \times R \right). \quad (16)
\end{aligned}$$

For defendant  $i$ , we can write  $R_i = R^v + R^c \rho_i$ , where  $\rho_i \equiv \rho(x_i)$  is the defendant's rearrest rate given his characteristics  $x_i$ .<sup>21</sup> Replacing  $R$  with  $R^v + R^c \rho_i$  in equation (17) then yields

$$L_i = W_{1i} \delta_1 + W_{2i} \delta_{2v} + (W_{2i} \rho_i) \delta_{2c} + W_{3i} \delta_{3v} + (W_{3i} \rho_i) \delta_{3c}, \quad (17)$$

where the auxiliary left hand side variable is given by  $L \equiv m^* f^* (1 - m f^*)$ , and the auxiliary right hand side variables and their coefficients are given by

$$W_1 = \left[ \frac{(1 - m^*) m^* f^*}{b^*} \right] \quad \delta_1 = \frac{\gamma_0}{\gamma_2}, \quad (18)$$

$$W_2 = [(1 - m^*) m^* f^*] \quad \delta_{2v} = R^v \quad \delta_{2c} = R^c, \quad (19)$$

$$W_3 = \left[ \frac{(1 - m^*) m^*}{b^*} \right] \quad \delta_{3v} = -\frac{\gamma_0}{\gamma_2} R^v \quad \delta_{3c} = -\frac{\gamma_0}{\gamma_2} R^c. \quad (20)$$

Notice that we have two overidentifying restrictions on this auxiliary specification: (i)  $\delta_1 \delta_{2v} + \delta_{3v} = 0$ , and (ii)  $\delta_1 \delta_{2c} + \delta_{3c} = 0$ .

Letting subscript  $i$  index individual observations, assume momentarily that for observed  $(b_i, x_i)$  and unobserved  $u_i$ , we observe the true probabilities  $F_i = F(b_i, x_i, u_i)$  and  $M_i = M(b_i, x_i, u_i)$ , regardless of whether bail is set optimally. Since each of these probabilities depends only on defendant behavior, knowing these values does not itself tell us anything about whether judges do choose bail in the way we have assumed: there is no guarantee that the observed bail level  $b_i$  is the solution to (4). If it isn't, then as we discussed above,

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<sup>21</sup>As noted above, the identification result in Theorem 1 allows the rearrest rate to vary with  $u$  as well as  $x$ . However, we found no empirical evidence that this is the case, so for simplicity we ignore this issue.



(16) won't generally hold when we replace  $f_i^*$  and  $m_i^*$ , the optimal values given  $(x_i, u_i)$ , with their observed counterparts  $F_i$  and  $M_i$ . Given that judges actually do choose bail optimally, though, we have seen that  $F_i = f_i^*$  and  $M_i = m_i^*$ . In that case,  $R$  could be estimated by calculating  $\delta_2$ , the coefficient on  $W_2$ , via least-squares estimation of equation (17). In addition, from (18) we see that when the model is correctly specified, so that the probabilities  $F_i$  and  $M_i$  are optimal, we have five functions of the three unknowns  $R^v$ ,  $R^c$ , and  $\gamma_0/\gamma_2$ . Thus with knowledge of the true probabilities  $F_i$  and  $M_i$ , we could test whether judge behavior is consistent with optimal bail setting given the objective function we have assumed.

In practice, we do not know the true values of  $F_i$  and  $M_i$ . Provided that we can estimate them consistently, though, we can still estimate the sample analog of (17), by replacing true values of the auxiliary variables and  $\rho_i$  with consistent estimates:

$$\widehat{L} = \widehat{W}_1\delta_1 + \widehat{W}_2\delta_{2v} + \widehat{W}_2\widehat{r}\widehat{h}\delta_{2c} + \widehat{W}_3\delta_{3v} + \widehat{W}_3\widehat{\rho}\delta_{3c} + v, \quad (21)$$

where hats denote estimated quantities and we replace  $M_i$  and  $F_i$  with their observable-at-the-optimum counterparts  $m_i$  and  $f_i$ . Thus, for example, the empirical analog of  $W_1$  for observation  $i$  is  $\widehat{W}_{1i} = b_i^{-1}[1 - \widehat{m}(b_i, x_i)]\widehat{m}(b_i, x_i)\widehat{f}(b_i, x_i)$ . The residual  $v$  in (21) is due to estimation error of  $\widehat{F}_i$ ,  $\widehat{M}_i$ , and  $\widehat{\rho}_i$ .<sup>22</sup> This discussion shows how we can consistently estimate the parameters  $R^v$  and  $R^c$  for any subpopulation within which the parameters  $P$  and  $\phi$ .

To estimate the conditional choice probabilities  $m(b_i, x_i)$  and  $f(b_i, x_i)$ , we use non-parametric, generalized product kernel regression methods proposed by Hall, Racine and Li (2004) and implemented in the **R** software environment via the **np** package by Hayfield and Racine (2008). We discuss relevant details of the nonparametric estimation in Appendix C. For the main text, we simply take as given that we have consistent estimates  $\widehat{m}_i$  and  $\widehat{f}_i$  of

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<sup>22</sup>Estimates of the  $\delta$  parameters based on (21) are consistent provided that  $\widehat{f}_i$  and  $\widehat{m}_i$  are consistent for  $F_i$  and  $M_i$ . Note that this is true even though functions of  $b_i$ ,  $F_i$ , and  $M_i$  appear on both sides of equation (17). We make no claim to estimating any type of partial or causal effect of  $(W_1, W_{2v}, W_{2c}, W_{3v}, W_{3c})$  on  $L$ , whatever that would even mean in this context. We are simply using the fact that, at the optimum under correct model specification, these variables must be related as discussed above. Only the linear projection relationship between these functions of the data are needed, and this relationship is precisely what can be estimated consistently using least-squares estimation of (21).

the conditional probabilities  $m(b_i, x_i)$  and  $f(b_i, x_i)$  for each observation  $i$ . To account for sampling variation due to the estimated nature of the variables in auxiliary equation (21), we use the bootstrap, using nonparametric Monte Carlo re-sampling.<sup>23</sup>

Our data on rearrests allow us to observe that a released defendant was either (i) not rearrested while on release, (ii) rearrested once, or (iii) rearrested two or more times. To estimate the rearrest rate  $\rho$ , we use a simple multinomial logit model among all those who made bail (pooling over race). We use the estimates from this model to predict the rearrest rate for all defendants, including those who do not make bail. We provide details of our rearrest-rate method in Appendix D

Before we turn to our econometric results, we emphasize the critical identifying role of our assumption that the unobserved heterogeneity term  $u$  is scalar. As discussed, our approach is robust to unobserved heterogeneity because the heterogeneity adds no information at the optimal bail level. If there were multiple heterogeneity dimensions, then this robustness would no longer hold, because bail optimality would no longer be sufficient to hold constant all unobserved heterogeneity. Mathematically, the problem is that we have access to only a single first-order condition to pin down unobserved heterogeneity. This is an important limitation of our approach (one that is shared by, e.g., Olley and Pakes’s (1996)). Our primary defense against the possibility of multi-dimensional unobserved heterogeneity is the fact that our empirical results do not reject the model’s overidentifying restrictions, as discussed below (the Olley and Pakes (1996) model also allows for overidentifying testing).

## 6 Econometric Results

In Table 3, we report estimates of  $\delta_1$ ,  $\delta_{2v}$ ,  $\delta_{2c}$ ,  $\delta_{3v}$ , and  $\delta_{3c}$  by county and race. These estimates come from OLS estimation of (21). Point estimates of  $\delta_1$  are negative, as predicted by the model, in six of the ten county-race cells, though most are estimated imprecisely. We report results for  $\delta_{2v}$  in the table’s second row. All of these estimates positive, as predicted by the model, and all of them are precise as well. Similarly, most estimates of  $\delta_{3v}$  in the fourth row

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<sup>23</sup>On each resample, we recalculate the estimated conditional choice probabilities and use these new estimates to re-estimate (21). We do not re-estimate the bandwidths used to generate kernel density estimates, due to the associated computational burden of re-doing cross-validation for bandwidth selection many times.

are precise, and nine of ten are positive as predicted. The table’s third and fifth rows report estimates of  $\delta_{2c}$  and  $\delta_{3c}$ . All of these estimates are imprecise, with all ten of the  $\delta_{2c}$  estimates being negative as predicted, and six of the ten  $\delta_{3c}$  estimates having the predicted negative sign.

In the bottom part of Table 3, we report estimates of statistics related to testing the model’s restrictions. If the model is correctly specified and judges determine bail optimally given their preferences concerning value of defendants’ freedom and the social cost of an FTA, then  $T_c \equiv \delta_1\delta_{2c} + \delta_{3c}$  and  $T_v \equiv \delta_1\delta_{2v} + \delta_{3v}$  should each equal zero up to sampling error. The county- and race-specific estimates of these statistics show that in general, they are imprecisely estimated, with 11 estimates negative and 9 positive. In the table’s final two rows, we report estimated p-values testing the null hypothesis that  $T_v = T_c = 0$  for the given county-race combination. We computed the first set of p-values, labeled “Conventional,” using the usual Wald tests. The lowest of these estimated p-values is 0.051, for whites in Dallas county. Taken by itself, this estimate suggests that the model’s restrictions are rejected. However, because we have two test statistics in each of 10 county-race cells, it is clear that there is no significant evidence rejecting the model’s restrictions, even for Dallas whites.

Given that the specification tests reported in Table 3 do not reject our model’s restrictions on the  $\delta$  parameters, we re-estimate the auxiliary regression model with this constraint imposed. Such constrained estimation allows us to obtain a unique estimate of the parameters  $\gamma_0/\gamma_2$ ,  $R^v$ , and  $R^c$  for each county-race cell. We impose the constraint by using nonlinear least squares (NLS) to estimate the equation

$$\widehat{L} = \widehat{W}_1 R + \widehat{W}_2 \frac{\gamma_0}{\gamma_2} + \widehat{W}_3 \left( -\frac{\gamma_0}{\gamma_2} \times R \right) + v, \quad (22)$$

where the parameters to be estimated are  $\frac{\gamma_0}{\gamma_2}$ ,  $R^v$ , and  $R^c$ .

We report these constrained NLS estimates in Table 4. While the estimates of  $R^c$  are imprecise, all 30 estimates reported in the table have the expected sign, and the estimates of  $\gamma_0/\gamma_2$  and  $R^v$  are highly precise. These results suggest that the model’s predictions given optimal bail setting are largely borne out by the data.

As our primary interest is in testing for racial discrimination against blacks, we report black-white differences in  $R^v$  estimates, together with estimated standard errors, in Table 5. The difference for Broward county is essentially zero, reflecting the very similar Table 4 estimates of  $R^v$  for Broward blacks and whites. Estimated black-white  $R^v$  differences for Cook and Los Angeles counties are also small in magnitude and statistically insignificant.

However, the estimated black-white difference in  $R^v$  is statistically significant for both Dallas and Harris counties.<sup>24</sup> In addition, the estimated differences in  $R^v$  are substantial in economic terms. To see this, we use the fact that  $P$  and  $\phi$  are assumed constant across race and observe that the black-white  $R^v$  difference relative to blacks'  $R^v$  estimate may be written

$$\frac{\Delta R^v}{R^{v,\text{black}}} = \frac{V^{\text{black}} - V^{\text{white}}}{P + V^{\text{black}}}. \quad (23)$$

The estimated levels of  $R^v$  for blacks in Dallas and Harris counties are 1.72 and 1.53, while the estimated black-white differences in  $R^v$  are -0.99 and -0.93. Thus, the Dallas/Harris black-white differences in  $R^v$  are roughly 60 percent of the counties' value of  $P + V^{\text{black}}$ . Put differently, under the assumption of optimal bail setting, judges in Dallas and Harris counties set bail as if they value blacks' value of lost freedom less than whites' by 60 percent of the total social costs associated with holding a black defendant until trial, which seems substantial to us.

Another way to express the relationship between  $V^{\text{black}}$ ,  $V^{\text{white}}$ , and  $P$  for Dallas and Harris counties is to set (23) equal to -0.6 and solve for  $V^{\text{black}}$ . This yields

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<sup>24</sup>Regarding statistical significance, the  $z$  ratios are -2.36 and -2.51 for the Dallas and Harris  $\Delta R^v$  estimates. As Table 5's "Conventional  $p$ -value" row shows, the conventional one-sided asymptotic  $p$ -values associated with these statistics are 0.009 and 0.006. The row labeled "Uniform  $p$ -value" reports higher, but still statistically significant  $p$ -values when we account for the multiple number of  $\Delta R^v$  estimates calculated. To estimate the uniform  $p$ -values, define  $S^l = \max_{\{j\}} \{(\widehat{\Delta R}^{v,jl} - \overline{\Delta R}^{v,j})/\widehat{\sigma}^j\}$ , where  $\widehat{\Delta R}^{v,jl}$  is the estimate of  $\Delta R^v$  for county  $j$  on bootstrap replication  $l$ , and  $\overline{\Delta R}^{v,jl}$  and  $\widehat{\sigma}^j$  are the mean and standard deviation of the realized bootstrap distribution of the  $\widehat{\Delta R}^{v,jl}$  estimates. We calculate our uniform  $p$ -value for county  $j$  as the share of the bootstrap replications for which  $S^l < \widehat{\Delta R}^{v,j}/\widehat{\sigma}^j$ . This method preserves the cross-county dependence structure in  $\Delta R^{v,j}$  estimates while also placing all estimates on the same scale by normalizing their marginal standard deviations to one. Finally, by recentering the estimates when constructing  $S^l$ , we are able to impose the null hypothesis of no discrimination.

$$V^{\text{black}} = 0.625V^{\text{white}} - 0.375P. \quad (24)$$

Thus, even if the pecuniary costs of jailing defendants were zero, our results would suggest that judges in Dallas and Harris counties set bail as if blacks' lost freedom is worth less than two-thirds of whites' lost freedom. To add further perspective, we follow Abrams and Rohlfs (2010, henceforth, AR) and use a figure of \$106 per day as the daily pecuniary cost of incarcerating a prisoner;<sup>25</sup> We use an estimate of 82 days to estimate the number of days a defendant would spend incarcerated as a result of not making bail.<sup>26</sup> Thus for our parameter  $P$ , we use \$106 per day  $\times$  82 days, or a total of \$8,692. Since 0.375 times this figure is \$3,260, we have  $V^{\text{black}} = 0.625V^{\text{white}} - \$3,260$  for Dallas and Harris counties over an 82-day period.

If we assume that judges never place a negative value on lost freedom, so that they never gain utility from locking up black defendants, then we can find a lower bound for  $V^{\text{white}}$  by setting  $V^{\text{black}} = 0$ . Setting the right hand side of (24) equal to zero and solving yields a lower bound of \$5,216 for  $V^{\text{white}}$  over 82 days, which translates to roughly \$64 per day. Since the black-white gap in  $V$  grows with  $V^{\text{white}}$ , this difference of \$64 per day is a lower bound for the black-white difference in the value of lost freedom for Dallas and Harris counties.<sup>27</sup> One

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<sup>25</sup>This figure is based on the figure of \$9,500 for 90 days that AR report as the midpoint of pecuniary jailing cost estimates reviewed by Levitt (1996). This figure is expressed in 2003 dollars.

<sup>26</sup>The SCPS reports the number of days from arrest to adjudication. We found very large differences in this variable's distribution according to whether a defendant makes bail. For example, among those who do not make bail, the median number of days between arrest and adjudication was 40, while it was 133 among the 1,497 defendants in our sample who do make bail. We use only those who did not make bail to approximate the expected number of days a defendant would spend incarcerated while awaiting trial if he did not make bail. To estimate the mean number of days between arrest and adjudication for these defendants, we need to account for the fact that the SCPS contains follow-up information for only about a year. Four observations in our sample of those who are held over for trial have a duration listed as "more than one year," while an additional 47 observations have arrest-to-adjudication duration listed as pending. If we assume that these 51 right-censored cases closed at 366 days, the average number of days from arrest to adjudication would be 78.8. If we instead account for right-censoring by assuming that arrest-to-adjudication duration is distributed exponentially and use maximum likelihood estimation to estimate the exponential parameter, the result is -4.40. An exponential distribution with this parameter has mean  $\exp(4.40) = 81.5$ , so we use a mean duration of 82 days. This calculation ignores the fact that a small amount of time elapses between arrest and bail hearings, while a larger amount of time may pass before a defendant is able to gather bail or bond money. However, the average time between arrest (not bail hearing) and pre-trial release among those who do make bail is only about 9 days. Since only a bit more than 40 percent of our sample makes bail, the net effect of these biases is likely only a few days on average, so we ignore these issues.

<sup>27</sup>While it is not our primary focus, we can use this lower bound on  $V^{\text{white}}$  to compute lower bounds for  $\phi$ , the direct social costs associated with a failure to appear, and  $c$ , the costs of crime associated with

might surmise that some of the value of lost freedom gap is due to the black-white earnings gap. We do not have employment earnings data, so we cannot consider this possibility directly. However, AR report that in their sample, foregone wage earnings work out to only about \$10.50 per day (this small earnings level is due to the fact that 76% of their sample is unemployed). Thus it seems unlikely that a \$64 per day racial difference in the value of lost freedom can be explained only through judicial notice of differences in labor market opportunities.<sup>28</sup>

Our estimates of  $R^v$  in Table 5 implicitly involve the restriction that  $c$ , the social cost of crimes associated with a rearrest, is the same for all defendants in a race-county cell. One might plausibly expect these social costs to vary with the type of charge for which the defendant has been indicted. If so, then our estimates of  $R^v$  could be misleading. We address this possibility by allowing  $c$  to take on separate values according to the defendant's charged offense type.

To do so, we reestimate the sample analog of (17) with  $\rho_i$  interacted with four offense-type dummies. This yields four separate estimates of  $R^c$  for each race-county cell. The 40  $R^c$  estimates (two race groups times five counties times four offense types) from these specifications were very imprecisely estimated, which is not surprising given the imprecision of the  $R^c$  estimates reported in Table 5. The black-white differences in  $R^v$  are 1.02 for Broward; 0.02 for Cook; -0.06 for Dallas; -1.53 for Harris; and -0.31 for Los Angeles. The Broward

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an additional rearrest. Given  $R^{v,white} = (P + V^{white})/\phi$ , we have  $\phi = (P + V^{white})/R^{v,white}$ . Plugging in  $P = \$8,692$  and  $V^{white} \geq \$5,216$ , it follows that  $\phi \geq 13908/R^{v,white}$ . For Dallas and Harris counties, we estimate that  $R^{v,white}$  is 2.71 and 2.45, respectively. These estimates suggest a lower bound for  $\phi$  of between five and six thousand dollars. Furthermore, since  $R^c = -c/\phi$ , we have  $c = -R^c\phi$ , so that the lower bound for  $\phi$  allows us to use Dallas and Harris county estimates of  $R^c$  to calculate lower bounds for  $c$ . According to Table 5, race-specific estimates of  $R^c$  are roughly  $-1.27$  for blacks and  $-4.64$  for whites. Using these estimates together with  $\phi = \$5,500$  yields a lower-bound  $c$  estimate of \$6,985 for blacks and \$25,520 for whites. Since the magnitude of the black-white difference in  $c$  equals  $|c^{black} - c^{white}| = \phi(|R^{c,black}| - |R^{c,white}|)$ . Since this magnitude increases with  $\phi$ , we can say that in Dallas and Harris counties, the social costs of crimes associated with whites' rearrest are more than \$18,000 greater than those associated with blacks' rearrest. We note, though, that the estimates of  $R^c$  are very imprecise, which is one reason we do not focus more attention on them.

<sup>28</sup>Our \$64 per day lower bound on  $V^{white}$  is itself considerably larger than the roughly \$12 per day mean value that AR estimate for defendants' own value of lost freedom using a different sample and estimation method from ours. AR also discuss several comparisons for their estimated value of lost freedom. One is based on the foregone wage earnings for their sample, discussed above. Another comparison AR use is based on the literature on the value of a statistical life, which they calculate yields an estimate of roughly \$1,000 per day. Finally, they discuss the compensation offered by some states in case of wrongful imprisonment; this compensation ranges from \$4 to \$136 per day. (See footnote 20 on page 18 of AR for this discussion.)

estimate would be notable for its large magnitude and positive sign, but this estimate is very imprecise, carrying with it an estimated standard error of 0.91. The only statistically significant estimate of  $R^v$  is the -1.53 estimate for Harris county, whose estimated standard error of 0.47 yields a  $z$ -ratio of -3.26, significant at less than the 1 percent level using uniform critical values based on the appropriately rescaled and recentered bootstrap distribution of all five counties'  $\Delta R^v$  estimates.

We have a moderate preference in favor of the results in Table 5, and against the results that allow  $c$  to vary with offense type within race-county cells. We do believe it would be valuable to allow  $c$  to vary. But as we noted in the paragraph above, the estimates of  $R^c$  from specifications that allow this heterogeneity are very imprecise. In addition, the empirical bootstrap distribution of estimates of  $R^v$  provides some reason for concern. When asymptotic approximations are appropriate given the actual sample size, the mean of the empirical bootstrap distribution of a parameter should be similar to the actual estimate of that parameter. This is a particularly relevant practical concern for our paper, given our use of nonparametric methods for estimating conditional choice probabilities. The Harris county estimates are relatively close (the actual estimate is -1.53 and the bootstrap mean is -1.20), so we believe that result is robust to either specification. However, the actual and bootstrap mean estimates of  $\Delta R^v$  are quite different for some of the other estimates discussed in the previous paragraph. For example, the actual Dallas county estimate is  $-0.06$ , but the bootstrap mean is  $-0.74$ . The same type of comparison is considerably more favorable for focusing on our preferred results, those reported in Table 5: actual/bootstrap mean estimates are  $-0.20/-0.36$  for Cook;  $-0.04/-0.40$  for Broward;  $-0.99/-0.95$  for Dallas;  $-0.93/-0.86$  for Harris; and  $-0.002/0.03$  for Los Angeles.

## 6.1 Summary of results

We can sum up our econometric results with three key conclusions. First, estimates of  $\gamma_0/\gamma_2$  and  $R$ ,  $R^v$ , and  $R^c$  from constrained auxiliary specifications have the signs predicted by our model. Second, specification tests from our auxiliary projection relationships provide little evidence against the composite null hypothesis that each of the following simultaneously holds:

1. our model captures defendant behavior;
2. judges know  $(x, u, \gamma_0, \gamma_2, g_0(x), g_2(x))$  for each defendant;
3. judges set bail optimally given this knowledge.

Third, given the model, the point estimates suggest that there is evidence of bias against blacks in bail setting in Harris county, and likely also Dallas, though not in the other three counties. For Dallas and Harris counties, our preferred estimates imply that judges set bail as if they value whites' lost freedom at least \$64 per day more than they value blacks' lost freedom. We believe this is a sizable difference in economic terms, and one that is unlikely to be due only to any racial differences in labor market opportunities, given the highly selected nature of the population of felony defendants. Finally, we note that our estimates are somewhat imprecise, due in part to our accounting for the multiple-testing that is typically ignored in applied econometric research.

We conclude this section by addressing the possibility that judges behave in a way that is different from our model, but which is statistically indistinguishable from the way a judge would behave under this composite null hypothesis. This concern is relevant since we cannot practically characterize the power of our specification tests against all alternative models.

However, we believe our estimates would still be informative about racial discrimination in an important, counterfactual sense. Recall that our estimates of the conditional choice probabilities are nonparametric and do not require optimality of bail setting. An alternative view of our method, then, is that it tells us whether and how much actual bail setting involves discrimination relative to optimal bail setting. That is, whatever it is that judges are actually trying to do,<sup>29</sup> one might still accept our model as a reasonable description of what they would do if they behaved in a socially optimal way. Given our functional form assumptions on defendants' choice probabilities and how bail affects them, then, our estimates can be interpreted as consistent estimates of the  $R^v$  and  $R^c$  values that judges' behavior implicitly reveals. This interpretation is of more than academic interest, because

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<sup>29</sup>Posner (1993) argues that judges are ordinary people who respond to personal incentives, like their desire for leisure, rather than acting entirely as benevolent social planners. Helland and Klick (2007) provide empirical evidence that judges with more congested dockets exercise less oversight of attorney fee awards in class action lawsuits, in line with Posner's claim.



it is entirely possible that judges (i) do not wish to discriminate, but (ii) they nevertheless set bail using heuristics that have discriminatory effect.

## 7 Our Model and the Outcome-Test Literature

The idea of using outcomes to test for discrimination in other contexts has a long history. For example, Becker (1957) discusses the fact that wage discrimination requires paying different wages for given marginal product, which means that cross-group wage differences are not sufficient information to conclude that there is taste-based discrimination. In this context, the group-level average of workers' individual ratios of marginal productivity-to-wage would serve as an outcome measure.<sup>30</sup> Another application is to use mortgage profitability as an outcome measure to test for discrimination in credit markets, as Becker (1993, page 389) discusses.<sup>31</sup>

More recently, Knowles, Persico and Todd (2001, henceforth, KPT) have used the outcome test idea to test for whether police discriminate against racial minorities when deciding whether to search motorists stopped on the highway. KPT assume that police seek to maximize the number of "hits," i.e., searches that turn up contraband. Under this assumption, white and black "marginal searchees" must have the same probability of carrying contraband.

We now link this result to the idea behind Ayres and Waldfogel's (1994, henceforth, AW) paper on bail and racial discrimination. AW assume that a judge chooses a defendant's bail level in order to ensure that the conditional probability of FTA is no greater than some pre-specified constant,  $p$ , given that the defendant is released. Suppose momentarily that AW judges must either release a defendant or hold him until trial. Such judges will release a defendant if and only if  $F(0, u) \leq p$ .<sup>32</sup> Thus, if judges use the same value of  $p$  for blacks and whites, black and white "marginal releasees" will each have probability  $p$  of FTA. If judges discriminate against, say, blacks, then  $p^{\text{black}} < p^{\text{whites}}$ , so that the marginal black defendant faces a lower FTA probability.

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<sup>30</sup>Data on marginal productivity are quite difficult to collect; see Hellerstein and Neumark (1998) for an attempt to use plant-level productivity measures to assess labor market discrimination.

<sup>31</sup>Berkovec, Canner, Gabriel and Hannan (1994) use data on mortgage default rates among minority and non-minority borrowers for this purpose. For critiques of such work, see Yinger (1996) and Ayres (2005).

<sup>32</sup>We assume away variation in  $x$  for purposes of the discussion in this section.

In both the motorist-search and binary pretrial release-detain situations, however, there is an inframarginality problem. Even though marginal searchees and releasees have the same outcome value—contraband hit rates or FTA probability—when there is no racial discrimination, the average values of these outcomes need not be equal across race. For example, suppose that either the structure of the function  $F$  or the distribution of  $u$  differs across race in the binary release-or-detain case. Then the integral, over the distribution of  $u$ , of  $F(0, u)$  will generally differ across race, even though all marginal releasees have the same FTA probability, regardless of race. Thus, equal FTA probabilities for marginal releasees is insufficient for equal average FTA probabilities. In general, only the average FTA probability is identified, so the inframarginality problem wrecks the usefulness of comparing FTA rates across race.

There are different routes to solving the inframarginality problem. KPT do so by hypothesizing that motorists optimally choose whether to carry contraband, taking as given the probability that police will search them when they are stopped. KPT show that in Nash equilibrium, contraband-carry rates will be equal across all motorists who are searched with probability interior to  $(0, 1)$ . As a result, the inframarginality problem does not exist in Nash equilibrium.<sup>33</sup>

The inframarginality problem also disappears in the bail context under AW’s assumption on the judicial objective function. An AW judge’s optimal choice of bail  $b^{\text{AW}}(u)$  for a defendant with heterogeneity term  $u$  must satisfy  $F(b, u) \leq p$ . For some defendants,  $F(0, u) < p$ , and an AW judge will release these defendants with zero bail. For others,  $\lim_{b \rightarrow \infty} F(b, u) > p$ ,

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<sup>33</sup>Several papers have suggested plausible violations of KPT’s assumptions, under which the inframarginality problem reappears. For example, Antonovics and Knight (2004) show that if there is trooper heterogeneity in search costs, then “the test that KPT employ no longer distinguishes between preference-based discrimination and statistical discrimination” (page 10). Additionally, both Anwar and Fang (2006) and Antonovics and Knight (2004) have pointed out that the inframarginality problem reappears if there is systematic heterogeneity in how troopers behave as a function of troopers’ own race. Antonovics and Knight, Anwar and Fang, and Bjerk (forthcoming) all note that the same problem arises when, as Antonovics and Knight put it, “officers can observe some characteristic . . . that is correlated with the likelihood that the motorist is guilty, but that . . . is unknown to the motorist at the time that he or she decides to traffic drugs” (page 10). Dharmapala and Ross (2004) provide examples in which limits on troopers’ ability to monitor motorists, as well as differences in offense severity, can lead to equilibria in which some types of motorists always carry contraband, and they show that the link between average and marginal hit rates breaks down in such cases. All of these authors, and Close and Mason (forthcoming) as well, propose alternative tests of discrimination. Finally, Brock, Cooley, Durlauf and Navarro (2010) nest KPT’s assumed preference structure in a broader class for which KPT’s outcome test is generally uninformative.

so that no finite bail will convince such defendants to show up for trial with the desired probability.<sup>34</sup> An AW judge will deny bail to such defendants. For all other defendants, there must be a positive and finite value  $b^{\text{AW}}(u)$  such that  $F(b^{\text{AW}}(u), u) = p$ . Thus, given AW’s assumption on judge behavior, all defendants who receive a positive and finite bail level have the same probability of FTA at the optimal bail level, except to the extent that there is groupwise discrimination, in which case FTA probabilities will be equal within, but not across, groups.

As a result, there is no inframarginality problem when judges can choose bail continuously and behave according to the objective function AW assume. This fact helped motivate Ayres’s (2001) argument that the inframarginality problem may generally be surmountable when the decision variable is continuous, because then “every defendant [is] marginal” Ayres (2001, pp. 409-10). This claim can be read in either of two ways.

The first reading of Ayres’s conjecture is that outcome tests based on easily observed level variables like FTA are generally appropriate in any case with a continuous decision variable. Such a result would open up a wide array of settings to more robust testing for the presence discrimination. By rewriting the version of the judge’s first-order condition in (4), we see that at the optimal bail level,

$$F(b^*, x, u) = R^v + R^c \rho - \frac{M(b^*, x, u)F_b(b^*, x, u)}{M_b(b^*, x, u)}, \quad (25)$$

where we suppress the  $(x, u)$  argument of the function  $b^*$ . Consider a set of same-race defendants with the same rearrest rate, so that  $R^v + R^c \rho$  is a constant parameter for them. For such a set, the FTA probability at the optimal bail level can be constant across  $u$  only if the second term on the right hand side of (25) is constant across  $u$ . We prove in Appendix B that when  $u$  has a full-support continuous distribution, conditional on  $x$ , this term cannot generally be constant across  $u$  in our model. Thus, the first version of the Ayres conjecture does not hold when judges have the objective function we assume, which means it does not generally hold.

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<sup>34</sup>This result cannot happen in our model, however, since the latent utility of FTA converges to zero as  $b$  goes to infinity.

Consider now a second, more optimistic, reading of Ayres’s conjecture. As with the first one, the second reading holds that continuous decision variables eliminate the inframarginality problem. However, the second reading accepts that using outcome analysis to test for discrimination generally involves complicated outcomes whose estimation may require functional form assumptions. For example, our approach in this paper can be seen as a generalized form of outcome analysis. We estimate the probability of making bail and of FTA non-parametrically and then use assumptions concerning (i) functional form and (ii) optimal behavior to justify (iii) regarding these probabilities as  $M(b^*, x, u)$  and  $F(b^*, x, u)$  and (iv) expressing the derivatives  $M_b(b^*, x, u)$  and  $F_b(b^*, x, u)$  in terms only of the non-parametric conditional probability estimates. As a consequence, we are able to estimate all elements of (25), up to a finite-dimensional parameter vector.<sup>35</sup>

Thus, like the simple approach in AW or KPT, our approach uses outcome information together with behavioral assumptions to identify a parameter of interest. The only point of difference between our approach and AW’s, besides the fact that we assume different judicial objective functions, is that we must estimate outcome information, whereas AW (and KPT) can use raw data. Thus, the second reading gives broad credence to the Ayres conjecture. If one is willing to both assume the form of a decision-maker’s objective function and willing to assume enough behavioral structure, then the presence of continuous decision variables seems likely to eliminate inframarginality problems.

An additional question concerns which objective function is more appropriate in the present context, AW’s or ours. Of course, this is an empirical question. There is some empirical support for our model in that it passes the overidentification tests we use above. AW’s objective function is also testable in principle, because it requires FTA rates to be the same for all defendants of a given race, even when there is racial discrimination.

To test this assumption, we estimated an ordinary least squares model relating actual FTA among defendants who made bail to the same covariates that enter our nonparametric estimators discussed in Appendix C. Each model included a race dummy and a full set of county-by-offense type dummies to allow AW judges to set different levels of FTA by

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<sup>35</sup>Indeed, it is not difficult to write our judge’s problem in notation that represents a (slight) extension of Persico’s (2009) model, in which simple outcome tests generally exist.

county-offense type cells, and we allowed the covariates to have separate coefficients for blacks and whites. Under the null hypothesis that judges follow the AW objective function, the coefficients on all covariates, other than the ones involving county, race, and offense type dummies, should be zero.<sup>36</sup> The heteroskedasticity-robust  $F$ -statistic testing that all the relevant coefficients are zero has a p-value of 0.0359.

Thus, empirical evidence suggests that in our sample, judges are not choosing bail to equalize FTA across defendants, even within race. Given that our own model is not rejected by the data, we think the evidence favors our approach, at least for our data. In other samples representing other judges, AW’s objective function might be the right one; of course, some third objective function might also. On this point, we note that Brock et al. (2010) have shown persuasively that any method of testing for discrimination using observational data will require substantive assumptions on decision makers’ objectives.

## 8 Summary

We consider a model of optimal bail setting in which judges choose bail levels to trade off various costs. On one side are the costs of jailing defendants who do not make bail. These costs include both the pecuniary costs of running jails and the like, and the value judges place on freedom lost by (potentially innocent) defendants. On the other side are the social costs expected to be imposed by those defendants who make bail and are released pending trial. The optimal bail level is an implicit function of the defendant’s characteristics, including  $x$ , which both we and the judge observe, and  $u$ , which only the judge observes. The presence of heterogeneity that we cannot observe invalidates conventional cross-race comparisons of average bail levels, even conditional on  $x$ .

We develop an approach to testing for discrimination based on estimation of the judge’s first-order condition in an auxiliary regression. There are two key steps in making this estimation method practical. First, when there is a one-to-one mapping between optimal bail

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<sup>36</sup>Even though the dependent variable is binary, this model is correctly specified under the null hypothesis that judges follow AW’s objective function. This is true because (a) the conditional FTA probability given the optimal bail level and  $x$  must be unrelated to either  $b$  or  $x$  under the null, and thus (b) the dummy variables that appear in the null linear model saturate it fully.

and the unobserved heterogeneity term  $u$ , conditional on  $x$ , one need not know a defendant's  $u$  value to consistently estimate his conditional choice probabilities at the optimal bail level, given  $(b, x, u)$ . This result allows us to leave the distribution of  $u$  entirely unrestricted, even conditional on  $x$ .

Second, because partial derivatives of defendants' conditional choice probabilities can be written in terms of the levels of these probabilities under a multinomial logit structure, we do not need to directly estimate the partial derivatives of conditional choice probabilities with respect to bail. Instead, we are able to estimate these partial derivatives using nonparametric estimates of the levels of the conditional probabilities. We then recover the key parameter of interest,  $R^v$ , by estimating the first-order condition after re-writing it in terms of auxiliary variables that depend only on the level of bail and the conditional choice probabilities.

Our point estimates suggest that judges value freedom significantly less for blacks than whites in Harris county, and in our preferred specification, Dallas county as well. Back-of-the-envelope calculations suggest that judges in these counties value lost freedom substantially less for blacks than whites, with \$64 per day being a lower bound. For a defendant held until trial for a typical period of nearly three months, this range amounts to several thousand dollars' difference.

These findings suggest the possibility of substantial bias against blacks in bail setting. This result is important for multiple reasons. First, it is evidence of substantial judicial bias against blacks, which is of per se concern. Second, bail affects defendants' utility directly by affecting the probability that a defendant will lose his freedom for the potentially lengthy pre-trial period. Discriminatorily higher bails thus will make black defendants worse off in this sense. Finally, being held over might also affect the probability of conviction. Our results are therefore of substantial legal policy interest.

## A Identification of Parameters

The results in the main text require the identification only of  $R$  and the ratio  $\gamma_0/\gamma_2$ . For completeness, in this appendix we provide a formal proof of sufficient conditions for identification of these two quantities as well as for  $\gamma_0$ ,  $\gamma_2$ ,  $g_0(x)$ , and  $g_2(x) + u$ . In the case of  $g_0(x)$  and  $g_2(x) + u$ , the identification is pointwise. We note also that differences in  $u$  are

identified for two defendants with the same  $x$ .

**A 1** (Partially Linear Multinomial Choice Structure). *The indirect utilities received by a defendant who chooses  $(D_m, D_f) \in \{(0, 0), (0, 1), (1, 1)\}$  are given by (5).*

**A 2** (Nested Logit Structure). *The residuals  $(\epsilon_0, \epsilon_1, \epsilon_2)$  are jointly distributed according to a Type I Extreme Value distribution.*

**A 3** (Gamma Signs).  $\gamma_0 > 0 > \gamma_2$ .

**A 4** (Unobservable heterogeneity and rearrest). *The expected number of rearrests if the defendant is released is nondecreasing in  $u$ , i.e.,  $\partial \rho / \partial u \geq 0$ .*

**A 5** (Judge Information). *For any given defendant, judges know  $x$ ,  $\gamma_0$ ,  $\gamma_2$ ,  $g_0$ ,  $g_2$ , and  $u$ .*

**A 6** (Optimal Bail Setting). *Given the information in Assumption 5, judges set bail to minimize the social cost function  $q(b, x, u)$ .*

**Theorem 1** (Identification). *Suppose assumptions 1-6 hold. Then for any defendant for whom the optimal level of bail given  $(x, u)$  is positive and finite,  $R^v \equiv \frac{P+V}{\phi}$ ,  $R^c \equiv \frac{c}{\phi}$ , and  $\frac{\gamma_0}{\gamma_2}$  are identified given knowledge of the joint population distribution of  $(D_m, D_f, b^*, x)$ , where  $b^*$  is the optimal bail level given  $(x, u)$ . In addition:*

1. *the parameters  $\gamma_0$  and  $\gamma_2$  are identified;*
2. *the value  $g_0(x)$  is point-identified at any  $x$  in the support of the population;*
3. *the sum  $g_2(x) + u$  is identified at any  $(x, u)$  in the support of the population;*
4. *for given  $x$ , differences in  $u$  are identified.*

*Proof of Theorem 1.* We begin by stating and proving a lemma concerning the relationship between  $b$  and  $(x, u, \Theta)$  under the assumptions listed in the hypothesis of this theorem; we will suppress the notation concerning  $\Theta$  for exposition. Define  $e_0 = \exp[\gamma_0 \ln b + g_0(x)]$  and  $e_2 = \exp[\gamma_2 b + g_2(x)]$ . The probability of not making bail given  $(b^*, x, u)$  is  $1 - M(b, x, u) = \Pr(D_m = 0 | b, x, u) = e_0 / (e_0 + [1 + e_2])$ ; the probability of making bail and appearing is  $M(b, x, u)[1 - F(b, x, u)] = \Pr(D_m = 1, D_f = 0 | b, x, u) = 1 / (e_0 + [1 + e_2])$ , and the probability of making bail and failing to appear is  $M(b, x, u)F(b, x, u) = \Pr(D_m = 1, D_f = 1 | b, x, u) = e_2 / (e_0 + [1 + e_2])$ . We now state Lemma 1.

**Lemma 1.** *Suppose that assumptions 1-6 all hold. If the optimal bail level is finite and positive for a defendant with given  $(x, \underline{u})$ , then:*

1. *there exists a continuously differentiable function  $b^*$  on some neighborhood of  $(x, \underline{u})$  such that  $b^*(\underline{u}; x) = \underline{b}$ ;*
2.  *$\underline{u}$  is the unique value of  $u$  such that  $\underline{b} = b^*(\underline{u}; x)$  is optimal.*

*Proof of Lemma 1.* To establish item 1, it is enough to observe that all functions involved in the first-order condition for optimal bail are continuous, and that for a positive and finite optimal bail level, the first-order condition holds with equality.

To establish item 2, we begin by showing that if  $q_b(\underline{b}, x, u) = 0$ , then  $q_{bu}(\underline{b}, x, u) < 0$ . Suppressing the  $(b, x, u)$  argument of  $q$ ,  $M$ , and  $F$ , we redefine  $q = M(F - R)$ , which is just (2). Thus we have  $q_u = M_u(F - R) + M(F_u - R_u)$ . Using the multinomial logit functional forms for  $M$  and  $F$  conditional on  $(b, x, u)$ , it can be shown that  $M_u = (1 - M)MF$  and  $F_u = F(1 - F)$ . Thus,  $q_u = MF[(1 - M)(F - R) + 1 - F] - MR_u$ , or  $q_u = MF[1 - R - M(F - R)] - MR_u$ . Observing that the level of bail has no effect on any constituent part of  $R$ , note that  $R_b = R_{ub} = 0$ . Differentiating  $q_u$  with respect to  $b$ , we therefore have

$$q_{bu} = \{M_b F + F M_b\} [(1 - M)(F - R) + 1 - F] - MF \frac{\partial M(F - R)}{\partial b} - M_b R_u \quad (26)$$

$$= \{M_b F + F M_b\} [1 - R - M(F - R)] - MF q_b - M_b R_u. \quad (27)$$

The factor in braces is always negative, since  $M_b$  and  $F_b$  are each negative while  $F$  and  $M$  are each positive. When  $q_b = 0$ , the second term on the right hand side of (27) is zero. Next, observe that since  $R(x, u) = (P + V - c\rho(x, u))/\phi$ , with  $P$ ,  $V$ ,  $c$ , and  $\phi$  unaffected by  $u$ , we have  $R_u = -c\rho_u$ , which is non-positive by assumption 4; since  $M_b$  is negative,  $-M_b R_u$  is also non-positive. Thus, a sufficient condition for  $q_{bu}$  to be negative when  $q_b = 0$  is for the factor in square brackets to be positive, which we now establish is always true when  $q_b = 0$ . To do so, we use the fact that since  $q_b = M_b(F - R) + MF_b$ ,  $q_b = 0$  implies that  $F - R = -MF_b/M_b$ . It can be shown that  $F_b = \gamma_2 F(1 - F)$  and  $M_b = M(1 - M)[\gamma_2 F - \gamma_0/b]$ . Plugging these functions into the bracketed term in (27) yields

$$(1 - M)(F - R) + 1 - F = (1 - M) \times \frac{-M\gamma_2 F(1 - F)}{M(1 - M)[\gamma_2 F - \gamma_0/b]} + 1 - F \quad (28)$$

$$= (1 - F) \left[ \frac{-\gamma_2 F}{\gamma_2 F - \frac{\gamma_0}{b}} + 1 \right] \quad (29)$$

$$= \frac{1 - F}{\gamma_2 F - \frac{\gamma_0}{b}} \left[ -\frac{\gamma_0}{b} \right], \quad (30)$$

which is positive, since  $\gamma_2 < 0 < \gamma_0$  implies that both factors are negative. This establishes that whenever  $q_b = 0$ , we must have  $q_{ub} < 0$ . By symmetry of differentiation, this establishes  $q_{bu} < 0$ , and it follows by the implicit function theorem that  $\partial b^*/\partial u = -q_{bu}/q_{bb} > 0$  holds locally at every optimal bail level.

While we cannot establish general conditions for the global convexity of  $q$  in  $b$ , we can still establish the second part of the lemma, that there can be at most one value of  $u$  for which a given bail level is optimal, given  $x$ . Consider the function  $q_b(\underline{b}, x, u)$ , with  $\underline{b} = b^*$  being optimal for  $u = \underline{u}$ , given  $x$ . Since we have shown that  $q_{bu}(\underline{b}, x, \underline{u}) = 0$  given that  $\underline{b}$  is optimal at  $(x, \underline{u})$ , it follows that  $q_b(\underline{b}, x, \underline{u} + \epsilon)$  is negative for some sufficiently small  $\epsilon > 0$ . Let  $u'$  be the smallest  $u > \underline{u} + \epsilon$  such that  $\underline{b}$  is optimal at  $u'$  as well as at  $\underline{u}$ , and thus  $q_b(\underline{b}, x, u') = 0$ . Since  $q_b$  is continuous in  $u$ , we must have  $q_b(\underline{b}, x, u) < 0$  for all  $u$  in the interval  $(\underline{u} + \epsilon, u')$ ,



which means that  $q_b(\underline{b}, x, u')$  must be non-decreasing at  $u'$ . But this is a contradiction, since we established above that  $q_{bu}(\underline{b}, x, u') < 0$  if  $q_b(\underline{b}, x, u') = 0$ . This establishes that if  $\underline{b}$  is optimal given  $x$  and  $u = \underline{u}$ , it cannot be optimal for any  $u > \underline{u}$ ; the same argument in the other direction immediately establishes that  $\underline{u}$  must be the unique value of  $u$  for which  $\underline{b}$  can be optimal given  $x$ . We have thus established item 2 of the lemma.  $\square$

We next state and prove another lemma, which makes Lemma 1 useful for identification purposes.

**Lemma 2.** *Suppose that assumptions 1-5 hold, and suppose that the joint distribution of  $(D_m, D_f, b^*, x)$  is known, where the optimal bail level  $b^*$  given  $(x, u)$  is finite and positive. Then for fixed  $\Theta$ , at the optimal bail level,  $\Pr[D_m = d_m, D_f = d_f | b^*, x, u] = \Pr[D_m = d_m, D_f = d_f | b^*, x]$ . Furthermore,  $\Pr[D_m = d_m, D_f = d_f | b^*, x, u]$  is identified.*

*Proof of Lemma 2.* By Lemma 1, there exists a unique function  $h$  such that  $u = h(b^*; x)$ . Thus  $\Pr[D_m = d_m, D_f = d_f | b^*, x, u] = \Pr[D_m = d_m, D_f = d_f | b^*, x, h(b^*; x)]$ . For fixed  $\Theta$ , the latter conditional probability involves no more information than  $(b^*, x)$ . Identification of  $\Pr[D_m = d_m, D_f = d_f | b^*, x, u]$  follows because the joint population distribution function for  $(D_m, D_f, b^*, x)$  is known by hypothesis, proving the lemma.  $\square$

We now prove the theorem. Writing (17) as  $L = W'\delta$ , where  $W = (W_1, W_{2v}, W_{2c}, W_{3v}, W_{3c})'$ , it is clear that

$$\delta = (E[WW'])^{-1} E(WL), \quad (31)$$

so  $\delta$  is identified if the expectations on the right hand side of (31) are. Each element of the auxiliary data  $(L, W_1, W_{2v}, W_{2c}, W_{3v}, W_{3c})$  involves only functions of  $b^*$ ,  $m^*$ , and  $f^*$ . The expectation of any function involving these objects is identified, by Lemma 2 and the fact that the joint population distribution of  $(D_m, D_f, b^*, x)$  is known by hypothesis. Therefore, the vector  $\delta$  is identified. This immediately establishes identification of the parameters  $R_v$ ,  $R_c$ , and  $\gamma_0/\gamma_2$ , since they equal  $\delta_{2v}$ ,  $\delta_{2c}$ , and  $\delta_1$ , respectively. Because  $\delta_{3v}$  and  $\delta_{3c}$  are deterministic functions of the other delta parameters, they provide no further identifying information, and we must look elsewhere to separately identify  $\gamma_0$  and  $\gamma_2$ .

Next, observe that the model's multinomial logit structure implies that at  $b^*$ ,

$$\lambda(b^*, x) \equiv \ln \left( \frac{\Pr[D_m = 0 | b^*, x]}{\Pr[D_m = 1, D_f = 0 | b^*, x]} \right) = \gamma_0 \ln b^* + g_0(x), \quad (32)$$

with  $\lambda(b^*, x)$  being identified since each conditional probability in the parenthetical is identified, by Lemma 2. The conditional expectation given  $x$  of both sides of (32) is

$$E[\lambda(b^*, x) | x] = \gamma_0 E[\ln b^* | x] + g_0(x), \quad (33)$$

since  $g_0(x)$  depends only on  $x$ . Observe that both expectations are identified, by Lemma 2. Now eliminate  $g_0(x)$  by subtracting (33) from (32):

$$\lambda(b^*, x) - E[\lambda(b^*, x)|x] = \gamma_0(\ln b^* - E[\ln b^*|x]), \quad (34)$$

which eliminates  $g_0(x)$ . Multiplying both sides of (34) by  $(\ln b^* - E[\ln b^*|x])$ , taking expectations over the joint distribution of  $(b^*, x)$ , and rearranging then yields

$$\gamma_0 = \frac{E_{\{b^*, x\}} [(\lambda(b^*, x) - E[\lambda(b^*, x)|x]) (\ln b^* - E[\ln b^*|x])]}{E_{\{b^*, x\}} [(\ln b^* - E[\ln b^*|x])^2]}, \quad (35)$$

proving that  $\gamma_0$  is identified, since the expectations on the right hand side of (35) are identified, by Lemma 2. Since we have previously shown identification of the ratio  $\gamma_0/\gamma_2$ , identification of  $\gamma_0$  is also sufficient for identification of  $\gamma_2$ . This establishes item 1 of Theorem 1. Given  $\gamma_0$ , it is trivial to see from (33) that  $g_0(x)$  is point-wise identified for given  $x$ , which establishes item 2 of the theorem.

Finally, to prove identification of  $g_2(x) + u$  for given  $(x, u)$ , again use the model's multinomial logit structure to see that

$$\ln \left( \frac{F^*}{1 - F^*} \right) - \gamma_2 b^* = g_2(x) + u. \quad (36)$$

Since all elements of the left hand side are identified, the sum  $g_2(x) + u$  is as well, establishing item 3 of the theorem.

To establish item 4, consider data  $(b^*(x, u_1), x, u_1)$  and  $(b^*(x, u_2), x, u_2)$ . Taking the difference of (36) across the two data vectors,  $g_2(x)$  drops out, and we have

$$u_1 - u_2 = \left[ \ln \left( \frac{F_1^*}{1 - F_1^*} \right) - \gamma_2 b_1^* \right] - \left[ \ln \left( \frac{F_2^*}{1 - F_2^*} \right) - \gamma_2 b_2^* \right],$$

whose right hand side is identified by Lemma 2 and the identification of  $\gamma_2$ .  $\square$

## B A Counterexample to the Ayres Conjecture

If Ayres's conjecture were correct, then judges' optimal bail function  $b^*(\theta)$  would vary with  $(x, u)$  in such a way to ensure that  $F(b^*(u; x), x, u)$  were constant across defendants within racial groups. Using (25) and suppressing the  $(b^*, x, u)$  argument, we have that at the optimum,

$$F = R + \frac{\gamma_2 F(1 - F)}{(1 - M) [\gamma_2 F - \frac{\gamma_0}{b}]}. \quad (37)$$

Under the Ayres conjecture, the FTA probability must be constant, so the right hand side of (37) constant as well. Since  $R$  and  $\gamma_2$  are constant parameters, the conjecture can

be correct only if the denominator of (37) is also constant. Next, observe that when the conjecture is correct, we have  $\varphi \equiv \ln[F/(1-F)] = b^*\gamma_2 + g_2(x) + u$ , with  $\varphi$  being constant. The optimal bail level is then  $b^* = (\varphi - g_2(x) - u)/\gamma_2$ . For some fixed  $\lambda$ , denote  $D(\lambda)$  as that set of defendants for whom  $u = \lambda - g_2(x)$ . For these defendants, optimal bail is the constant value  $(\varphi - \lambda)/\gamma_2$ . For these defendants, then, the second term in the denominator of (37) equals  $\gamma_2 F - \gamma_0 \gamma_2 / (\varphi - \lambda)$ , which is constant, since  $\gamma_2$  and  $\gamma_0$  are fixed parameters and  $F$ ,  $\varphi$ , and  $\lambda$  all are constant by hypothesis. Thus, for the Ayres conjecture to hold in our model,  $(1 - M)$  must be constant for all defendants in the set  $D(\lambda)$ . In our model,  $M = (1 + e_2)/(1 + e_0 + e_2)$ . Since  $e_2$  must be constant for defendants in  $D(\lambda)$  when the Ayres conjecture holds,  $(1 - M)$  is constant if and only if  $e_0 = \gamma_0 \ln b^* + g_0(x)$  is also constant. Since all defendants in  $D(\lambda)$  have the same optimal bail level, this requires that all such defendants have the same  $g_0(x)$ . But this last requirement does not generally hold for fixed  $\lambda$ . For example, consider two defendants,  $i$  and  $j$ , with

1.  $g_2(x_i) \neq g_2(x_j)$ ;
2.  $u_j = u_i + g_2(x_i) - g_2(x_j)$ ;
3.  $u_i = \lambda - g_2(x_i)$ .

Conditions 2 and 3 imply that  $u_j = \lambda - g_2(x_j)$ , so both defendants are in  $D(\lambda)$ . However, since  $g_2(x_i) \neq g_2(x_j)$ , we must have  $x_i \neq x_j$ . Since the functions  $g_0$  and  $g_2$  are unrestricted in our model, this means that  $g_0(x_i) \neq g_0(x_j)$  is generally possible for two defendants in  $D(\lambda)$ , which would entail a contradiction.

This establishes that the Ayres conjecture cannot generally hold in our model, which means it cannot hold in general.

## C Nonparametric Kernel Estimation

In this appendix we briefly give an overview of the kernel nonparametric estimators of  $m(b, x) = \Pr(D_m = 1 | b, x)$  and  $f(b, x) = \Pr(D_f = 1 | D_m = 1, b, x)$  that we use to estimate the probabilities use in the auxiliary projection equation discussed in section 5.<sup>37</sup> Recall that  $D_m \equiv 1(\text{defendant makes bail})$ , while  $D_f \equiv 1(\text{defendant FTAs} | D_m = 1)$ , so that  $D = D_m + D_f$  provided that we set  $D_f = 0$  when  $D_m = 0$ .

We follow the convention of using capital letters to indicate random variables and lower case letters to indicate specific values they take on; we also use  $p$  as generic notation for densities. We observe that if  $p$  is the joint density of  $(D, B, X)$ , then the conditional density of  $D$  given  $(B = b, X = x)$  can be written

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<sup>37</sup>In this discussion, we use  $b$  rather than  $b^*$  to refer to the observed bail level. We do so because the non-parametric estimators of  $m(b, x)$  and  $f(b, x)$  are consistent regardless of whether judges choose bail optimally within the model we have specified. That is, optimal judge behavior is not necessary to estimate  $\Pr(D_m = 1 | b, x)$  and  $\Pr(D_f = 1 | D_m = 1, b, x)$  consistently. We emphasize, though, that these estimates are useful as deployed in the auxiliary projection equation only when bail is in fact chosen optimally, because only when bail is chosen optimally is  $u$  deterministically related to the observed (and thus optimal) bail level, given  $x$ .

$$p(d|b, x) = \frac{p(d, b, x)}{p(b, x)}. \quad (38)$$

Thus we can consistently estimate the conditional density of  $D$  given  $(B, X)$  if we consistently estimate both the joint density of  $(D, B, X)$  and the marginal density of  $(B, X)$ . The theory needed to estimate these functions nonparametrically is well developed. We follow the approach of using generalized product kernels suggested by Li and Racine (2007). Using general notation, let  $Z$  be a  $q \times 1$  random column vector, from whose probability distribution  $P$  an i.i.d. sample  $\{Z_i \in \mathbb{R}^q\}_{i=1}^n$  is sampled. Let  $Z_{ij}$  be the  $j^{\text{th}}$  row element of  $Z_i$ , and let  $z_j$  be the  $j^{\text{th}}$  row element of a fixed  $q \times 1$  column vector  $z$  that lies in the support of  $P$ . A generalized product kernel estimator for the associated density  $p(z)$  can be written

$$\hat{p}(z) = \frac{1}{n \times h_1 h_2 \dots h_q} \sum_{i=1}^n \prod_{j=1}^q k_j(Z_{ij}, z_j, h_j), \quad (39)$$

where  $h_j$  is a bandwidth parameter for the  $j^{\text{th}}$  element of the random vector  $Z$  and  $k_j$  is a kernel function for that element. Li and Racine (2007) provide conditions on  $h \equiv (h_1, h_2, \dots, h_q)'$  and the set of kernel functions  $\mathcal{K} \equiv \{k_1, k_2, \dots, k_q\}$  under which  $\hat{p}(z)$  is consistent for  $p(z)$ . A key issue is that the bandwidth parameters and kernel functions must be adapted to the types of random variables in  $Z$ . We can divide these variables into four groups:

- the dependent variable  $D$ , which is an unordered categorical variable equal to 0 for defendants who do not make bail, equal to 1 for those who make bail and do not FTA, and equal to 2 for those who make bail and do FTA;
- the bail level and the defendant's age, which we treat as continuous variables;
- a set of unordered categorical variables in  $x$ : offense category, county, year, and a variable indicating summarizing the defendant's history of prior FTAs (any, none, or inapplicable);
- a set of ordered categorical variables in  $x$ : the number of prior arrests, the number of prior prison terms, the number of prior jail terms, and whether the defendant had an active criminal case at the time of the current indictment. Also, in specifications including the private-attorney dummy, we treat it as ordered.

The kernel function used for each type of random variable must be appropriate to that type. For each random variable type just described, we use the default kernel types implemented in Hayfield and Racine's (2008) **npcdensbw** command. When the  $j^{\text{th}}$  variable is discrete and unordered, with  $C_j$  values in its support, we use the Aitchinson and Aitken kernel:

$$k_j(Z_{ij}, z_j, h_j) = \begin{cases} 1 - h_j, & \text{if } Z_{ij} = z_j, \\ \left(\frac{h_j}{C_j - 1}\right), & \text{if not.} \end{cases} \quad (40)$$

Notice that when the bandwidth equals  $(C_j - 1)/C_j$ ,  $k_j$  will have the value  $(1/C_j)$  regardless of  $Z_{ij}$ 's value. This means that the  $j$ [th] variable is treated as having uniform density for purposes of the joint-density computation. As discussed in, e.g., Li and Racine (2007), this result is a feature rather than a bug, since it allows the bandwidth-selection algorithm to endogenously treat a variable as irrelevant (the selection algorithm is constrained not to choose a value for  $h_j$  above this value).

When the  $j^{\text{th}}$  variable is discrete and ordered, we use the Wang and van Ryzin kernel with bandwidth  $h_j$ :

$$k_j(Z_{ij}, z_j, h_j) = \begin{cases} 1 - h_j, & \text{if } Z_{ij} = z_j, \\ \frac{1}{2}(1 - h_j)h_j^{|Z_{ij} - z_j|}, & \text{if not.} \end{cases} \quad (41)$$

Again, if  $h_j = 0$ , only observations with  $Z_{ij} = z_j$  would contribute to the density estimate for  $z_j$ . In addition, when  $h_j$  equals the maximum allowed value of 1, the “density estimate” would be zero for all observations. We do encounter some instances of this situation. We interpret such cases as telling us that the variable in question is irrelevant, so we simply set  $k_j(Z_{ij}, z_j, 1) = 1$ , rather than 0, for all such cases.

Finally, when the  $j^{\text{th}}$  variable is continuous, we use the Gaussian kernel with bandwidth  $h_j$ :

$$k_j(Z_{ij}, z_j, h_j) = \frac{1}{\sqrt{2\pi}} \exp \left[ -\frac{1}{2} \left( \frac{Z_{ij} - z_j}{h_j} \right)^2 \right]. \quad (42)$$

Given the set of kernel functions  $\mathcal{K}$ , we choose the bandwidth vector  $h$  optimally via maximum-likelihood cross-validation with the **npcdensbw** command implemented as part of Hayfield and Racine’s **np** package (Hayfield and Racine (2008)). We refer readers to Li and Racine (2007) for further details on product kernel estimation.

We estimate separate bandwidth parameters for blacks and whites (estimates appear in Appendix Table 1). We calculate the associated estimates of  $m(b_i, x_i)$  and  $f(b_i, x_i)$  by using these bandwidth estimates to evaluate (39) separately for  $z = (d, b_i, x_i)$ ,  $d \in \{0, 1, 2\}$ . We then use (38) for the appropriate choice of  $d$  to determine the implied estimates of  $m(b_i, x_i)$  and  $f(b_i, x_i)$ . The resulting estimates are what we use to form the generated variables  $L_i$ ,  $W_{1i}$ ,  $W_{2i}$ , and  $W_{3i}$  that we use in the auxiliary projection equation.

Finally, note that while we estimate separate bandwidths by race, we pool observations across county and offense type when estimating the bandwidths and implied estimates of  $m(b_i, x_i)$  and  $f(b_i, x_i)$ . We do so to avoid excessive variability in bandwidth estimation. Because we use data-driven bandwidths, we do not believe that our data pooling will be problematic; if, for example, two counties have very different densities of other variables,

then the resulting bandwidth estimates should account for that fact, up to sampling error.

## D Estimating Rearrest Rates

We assume that any defendant rearrested two or more times is rearrested exactly two times, so that our estimated rearrest rate for our defendant is the sum of his probability of getting rearrested once and twice his probability of getting rearrested at least twice. The mean observed values of this variable among those who made bail varied considerably across counties: Broward defendants had an average of 0.33 arrests while on release; Cook defendants had an average of 0.04; Dallas defendants, 0.07; Harris defendants, 0.07; and Los Angeles defendants, 0.15.

To estimate the multinomial logit model, we include the following as explanatory variables: age and its square; dummies for the defendant’s original charged offense being of type drug, property, or public order; four county dummies; a dummy for year; a variable indicating the defendant’s number of prior arrests if that number was less than 10 and a dummy variable indicating whether the defendant was previously arrested at least 10 times; and the number of prior prison terms.<sup>38</sup> We also investigated the possibility that the unobservable term  $u$  enters the rearrest rate function, so that  $\lambda_i = \lambda(x_i, u_i)$ . Given the unique mapping result for  $u$ , we have  $u_i = h(b^*(u_i; x_i); x_i)$ , so that  $\lambda_i = \lambda(x_i, h(b_i; x_i))$  when bail is set optimally. Thus, including bail as an explanatory variable in the rearrest model would control for the presence of  $u$  in this model. Because the bail variable’s coefficient was far from statistically significant when we included bail in the rearrest model, we conclude that if bail setting is done optimally according to our model, then judges do not have any more information than researchers about rearrest rates conditional on a defendant’s release.<sup>39</sup> In addition, we found that a dummy variable indicating defendant’s race had trivially small and statistically insignificant coefficients in the multinomial logit model for rearrest; we therefore excluded this dummy variable from this model. Appendix Table 2 displays the coefficients from our multinomial logit model for rearrest.

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<sup>38</sup>Before using the parametric multinomial logit model, we investigated the performance of a nonparametric approach analogous to the one we use to estimate  $m_i$  and  $f_i$ . The nonparametric approach greatly overpredicted rearrest rates among those who were actually released; we believe this poor performance is due to the small share—roughly 9 percent—of released defendants who are ever rearrested. Thus we chose to use a parametric multinomial logit to predict rearrest rates.

<sup>39</sup>The estimated bandwidth for bail from our (disfavored) nonparametric estimates also suggested that conditional rearrest rates are unrelated to bail.

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Table 1: Summary Statistics for Estimation Samples(generating time: Sun Feb 13 10:50:47 2011 from file *summary-stats.arv.*)

	Violent		Property		Drug		Public Order	
	Black	White	Black	White	Black	White	Black	White
Bail (in \$1000s)	35.9 (30.4)	29.0 (28.6)	28.3 (28.2)	22.6 (26.7)	29.0 (27.5)	16.1 (19.6)	30.3 (30.4)	19.0 (22.0)
Regression-adjusted difference	-0.14		1.39		6.37		0.63	
p-value for $H_0$ : no difference	0.95		0.41		0.00		0.85	
<u>Outcomes</u>								
Made bail	0.40	0.53	0.35	0.48	0.34	0.57	0.45	0.63
FTA, given made bail	0.10	0.14	0.14	0.19	0.25	0.20	0.16	0.20
<u>Background characteristics</u>								
Age in years	29.9 (10.5)	33.5 (11.0)	31.7 (10.1)	29.8 (9.4)	32.3 (10.4)	32.6 (9.5)	30.2 (9.6)	33.3 (11.5)
Any prior FTA	0.32	0.21	0.45	0.34	0.45	0.30	0.41	0.19
No possible prior FTA	0.26	0.33	0.14	0.29	0.11	0.26	0.14	0.28
Any prior arrests	0.74	0.67	0.86	0.71	0.89	0.74	0.86	0.72
At least 10 prior arrests	0.22	0.16	0.36	0.26	0.34	0.27	0.33	0.19
Any prior prison	0.24	0.18	0.36	0.22	0.43	0.21	0.34	0.23
Any prior jail	0.45	0.44	0.59	0.42	0.50	0.46	0.56	0.46
Active CJ status	0.30	0.15	0.41	0.31	0.29	0.27	0.33	0.12
<u>Attorney type</u>								
Private attorney	0.24	0.38	0.16	0.28	0.13	0.28	0.26	0.39
Public defender	0.40	0.29	0.58	0.45	0.57	0.41	0.47	0.28
Court-appointed	0.17	0.16	0.15	0.15	0.18	0.16	0.13	0.18
Data missing	0.18	0.17	0.11	0.12	0.11	0.15	0.13	0.16
<u>County and Year</u>								
Broward	0.13	0.17	0.09	0.12	0.08	0.15	0.08	0.10
Cook	0.19	0.13	0.29	0.21	0.50	0.20	0.43	0.29
Dallas	0.18	0.16	0.15	0.11	0.06	0.12	0.07	0.11
Harris	0.21	0.35	0.17	0.23	0.21	0.24	0.17	0.34
Los Angeles	0.28	0.18	0.30	0.33	0.14	0.29	0.25	0.17
Fraction from year 2000	0.54	0.49	0.53	0.51	0.57	0.55	0.41	0.34
N	277	146	418	255	853	295	143	83

*Note:* See text for discussion of variable definitions. Figures in parentheses are standard deviations for continuously distributed variables.

Table 2: Average Bail By County (generating time: Mon Mar 7 20:39:29 2011 from file *bail-by-county ara*, table 1.)

	Black		White		Difference
	5,258 (934)		5,350 (960)		
Broward					-93 (1,383)
N	161		109		270
Cook	39,876 (1,089)		27,359 (2,259)		12,517 (2,524)
N	695		158		853
Dallas	13,691 (986)		11,856 (1,299)		1,835 (1,648)
N	206		111		317
Harris	12,909 (732)		11,028 (848)		1,880 (1,143)
N	340		213		553
Los Angeles	46,996 (1,515)		38,556 (1,853)		8,440 (2,432)
N	361		213		574

*Note:* Figures reported only for our estimation sample. Standard errors in parentheses.

Table 3: Auxiliary Parameter Estimates From NP Estimation of Choice Probabilities and Unconstrained OLS Estimation of the Auxiliary Equation, Using Individual Rearrest Probabilities  
(generating time: Mon Mar 7 16:31:58 2011 from file *aux-results-by-race-rearrest.ara*, table 1.)

	Broward		Cook		Dallas		Harris		LA	
	Black	White	Black	White	Black	White	Black	White	Black	White
<u>Aux OLS estimates</u>										
$\delta_1 (= \frac{\gamma_0}{\gamma_2 \times 1000} < 0)$	-0.83 (0.61)	-0.34 (1.21)	-3.48 (2.45)	1.70 (3.46)	0.21 (0.81)	4.87 (2.04)	-0.62 (0.52)	-0.91 (1.63)	0.18 (2.39)	-6.18 (4.62)
$\delta_{2v} (= R_v > 0)$	2.90 (0.58)	2.44 (0.68)	1.56 (0.16)	1.89 (0.29)	1.73 (0.20)	2.86 (0.41)	1.59 (0.13)	2.46 (0.36)	1.33 (0.18)	1.40 (0.17)
$\delta_{2c} (= R_c < 0)$	-2.13 (1.16)	-0.03 (2.19)	-0.51 (4.58)	-2.83 (9.34)	-1.90 (2.39)	-12.11 (8.78)	-1.50 (0.98)	-4.08 (2.94)	-0.54 (0.87)	-0.69 (0.83)
$\delta_{3v} (= -\frac{\gamma_0}{\gamma_2 \times 1000} R_v > 0)$	0.41 (0.18)	0.25 (0.23)	1.62 (0.53)	0.43 (0.67)	0.21 (0.14)	-0.59 (0.33)	0.19 (0.07)	0.40 (0.26)	1.13 (0.81)	4.28 (1.52)
$\delta_{3c} (= -\frac{\gamma_0}{\gamma_2 \times 1000} R_c < 0)$	0.10 (0.40)	-0.32 (0.41)	-9.60 (25.20)	-2.57 (16.13)	0.82 (2.50)	4.02 (4.48)	0.13 (0.51)	-0.43 (3.02)	-0.78 (3.69)	-1.23 (6.34)
<u>Model restrictions</u>										
$T_v = \delta_1 \times \delta_{2v} + \delta_{3v} = 0$	-2.01 (1.62)	-0.57 (2.97)	-3.82 (3.52)	3.64 (5.92)	0.57 (1.29)	13.36 (5.64)	-0.79 (0.79)	-1.84 (3.68)	1.37 (2.69)	-4.39 (5.45)
$T_c = \delta_1 \times \delta_{2c} + \delta_{3c} = 0$	1.88 (1.49)	-0.31 (3.45)	-7.82 (35.09)	-7.39 (40.85)	0.42 (3.42)	-55.00 (43.09)	1.05 (1.09)	3.28 (10.17)	-0.88 (4.04)	3.05 (9.71)
Conventional $p$ -value	0.418	0.977	0.454	0.814	0.858	0.051	0.571	0.853	0.874	0.719

*Notes:*

- Expressions in parentheses in far-left column are model parameter values and signs under the assumption of correct model specification.
- Estimated standard errors appear in parentheses; all standard errors are based on 996 bootstrap replications.
- Conventional  $p$ -value is from usual two-sided test, based on asymptotic normality, against the column-by-column null hypothesis that the model's restrictions hold, with no correction for multiple testing.
- Uniform  $p$ -value is from two-sided test against the same null hypothesis, using bootstrap distribution to correct for multiple testing (see text for details).

Table 4: Auxiliary Estimates of  $\frac{\gamma_0}{\gamma_2}$ ,  $R_v$ , and  $R_c$  Based on NP Estimation of Choice Probabilities and Constrained (NLS) Estimation of the Auxiliary Equation, Using Individual Rearrest Probabilities  
(generating time: Mon Mar 7 16:31:59 2011 from file *aux-results-by-race-rearrest.ara*, table 2.)

	Broward		Cook		Dallas		Harris		LA	
	<u>Black</u>	<u>White</u>	<u>Black</u>	<u>White</u>	<u>Black</u>	<u>White</u>	<u>Black</u>	<u>White</u>	<u>Black</u>	<u>White</u>
$\frac{\gamma_0}{\gamma_2 \times 1000}$	-0.18 (0.12)	-0.05 (0.04)	-0.06 (0.42)	-0.36 (0.15)	-0.19 (0.07)	-0.13 (0.06)	-0.11 (0.03)	-0.11 (0.08)	-1.00 (0.36)	-2.71 (0.77)
$R_v$	2.58 (0.61)	2.63 (0.57)	1.79 (0.19)	1.99 (0.27)	1.72 (0.18)	2.71 (0.40)	1.53 (0.11)	2.45 (0.37)	1.35 (0.15)	1.35 (0.13)
$R_c$	-1.82 (0.86)	-0.88 (1.16)	-4.25 (4.16)	-3.85 (6.85)	-1.39 (2.14)	-4.86 (4.85)	-1.15 (0.76)	-4.43 (2.07)	-0.52 (0.68)	-0.81 (0.60)

*Notes:*

- Expressions in parentheses in far-left column are model parameter values and signs under the assumption of correct model specification.
- Estimated standard errors appear in parentheses; all standard errors are based on 996 bootstrap replications.

Table 5: Estimated Black-White Difference in  $R_v$ , Pooled Over Crime Type, Based on NP Estimation of Choice Probabilities and Constrained NLS Estimation of the Auxiliary Equation, Including Individual Rearrest Probabilities  
(generating time: Mon Mar 7 18:13:46 2011 from file *aux-dif-results-rearrest.ara*, table 3.)

	Broward	Cook	Dallas	Harris	LA
$\Delta R_v$	-0.04 (0.80)	-0.20 (0.33)	-0.99 (0.42)	-0.93 (0.37)	-0.00 (0.19)
Test of $H_0 : \Delta R_v = 0$ against $H_a : \Delta R_v < 0$ , using					
Conventional $p$ -value	0.478	0.272	0.009	0.006	0.497
Uniform $p$ -value	0.939	0.748	0.067	0.049	0.946

- Notes:
- Estimated standard errors appear in parentheses; all standard errors are based on 999 bootstrap replications; see text for bootstrap details.
  - Uniform  $p$ -value is one-sided and based on bootstrap distribution.



Appendix Table 1: Bandwidth results

	Upper Bound	Black Sample	White Sample
<i>Unordered categorical variables:</i>			
Dependent variable	0.6667	0.0181	0.0247
Most serious offense	0.9333	0.7366	0.8658
County	0.8000	0.2421	0.4997
Year	0.5000	0.2737	0.1364
Prior FTAs	0.6667	0.6667	0.2733
<i>Ordered categorical variables:</i>			
Prior arrests	1.0000	0.8368	1.0000
Prior prison terms	1.0000	0.4650	0.3049
Prior jail terms	1.0000	0.8011	0.7860
Criminal justice status	1.0000	0.9450	0.1240
<i>Continuous variables:</i>			
Bail	$\infty$	8859.5520	9874.7580
Age	$\infty$	21.4947	6982694.0000

See appendix on non-parametric estimation for more details.



Appendix Table 2: Estimated Coefficients From Rearrest Multinomial Logit Model  
(generating time: Mon Mar 7 16:17:22 2011 from file *numrearrr.ara*, table 1.)

	One Rearrest	Two or More Rearrests
Age	-0.17 (0.07)	-0.10 (0.10)
Age squared	0.0020 (0.0009)	0.0013 (0.0014)
Property offense	-0.40 (0.46)	1.62 (1.08)
Drug offense	0.66 (0.37)	1.83 (1.05)
Public order offense	-0.29 (0.62)	1.82 (1.15)
Cook County	-3.32 (0.64)	-2.48 (0.67)
Dallas County	-1.47 (0.49)	-2.15 (1.07)
Harris County	-1.35 (0.40)	-1.65 (0.69)
Los Angeles County	-0.51 (0.36)	-1.20 (0.55)
Year is 2002	-0.16 (0.28)	0.39 (0.43)
Number of prior arrests	0.14 (0.06)	0.24 (0.09)
At least 10 prior arrests	-0.93 (0.49)	-0.50 (0.67)
Number of prior prison terms	0.38 (0.19)	0.11 (0.26)
Constant	0.78 (1.17)	-3.50 (2.08)
N		1,034

*Note:* Figures in parentheses are estimated standard errors.